Data Analysis and Decision Making - II

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Lecture – 49
Demand Model

Good afternoon everyone, this is Priyanka Sharma. I am a PhD student, working under Professor Raghu Nandan Sengupta who is the instructor for this 3 module course Data Analysis and Decision Making. Currently we are in part 2 of this module.

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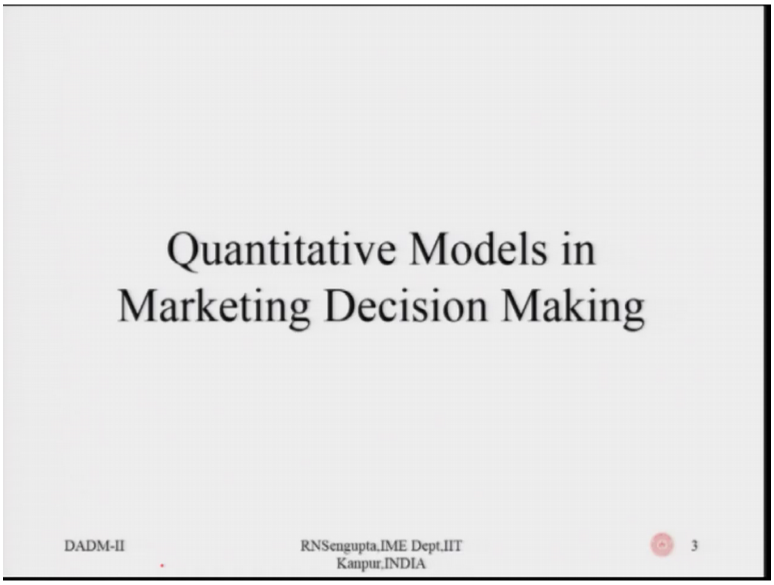

So far, professor Sengupta has discussed a lot of decision making techniques for example, AHP, utility theory and other multi criteria decision making models, but I am going to cover in current lecture and the one we will do after this is how these decision making techniques are utilized in marketing models. In marketing is an applied field where a lot of decision making is involved in terms of understanding customer demand, in sales forecasting, in planning pricing strategies so on and so forth.

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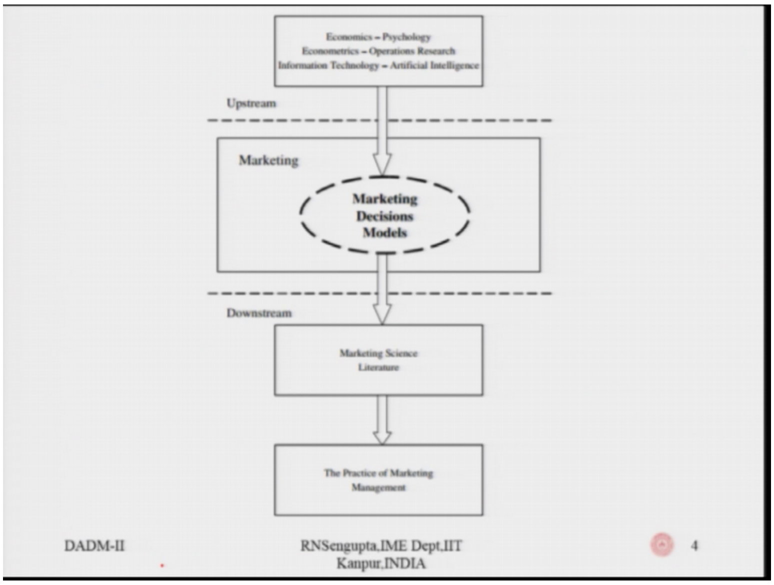

So, if you try to understand how does these models come into picture? So, marketing utilizes the concepts of econometrics, economics and other statistic techniques to marketing decision models and which are applied downstream in making those strategies which are firm adopts. And then, it also forms part of the marketing literature in the broader sense of academic and scholarly contribution in theoretical terms.

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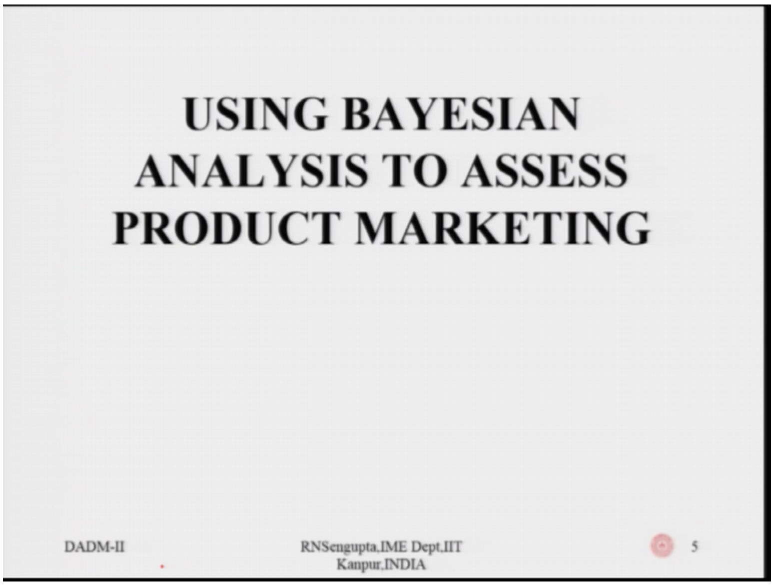

So, to begin with I will discuss what is known as Bayesian framework and how it can be utilized in assessing product marketing.

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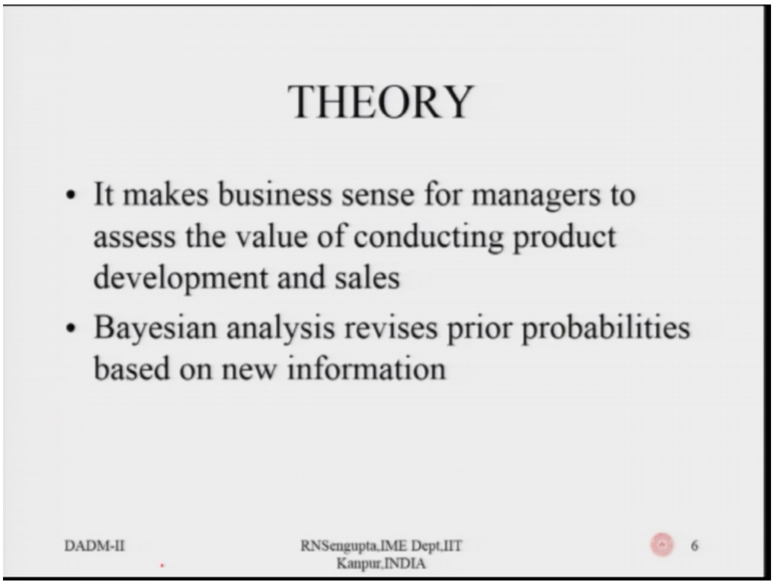

I let us start with a very simple example where we have to make pricing decision, before we launch a product and it is very important for business managers and firms to understand, how the demand is going to be for this particular product, for certain period of time. Whether it is going to be profitable or not? Because, if it is not profitable, then they can invest that amount in some in building a product which is more valuable to the end customers and hence to the firm in terms of revenues and sustained growth.

Bayesian analysis as you have already learned and takes into account the prior distribution or prior information about say demand, about sales, about pricing strategies to make predictions about future.

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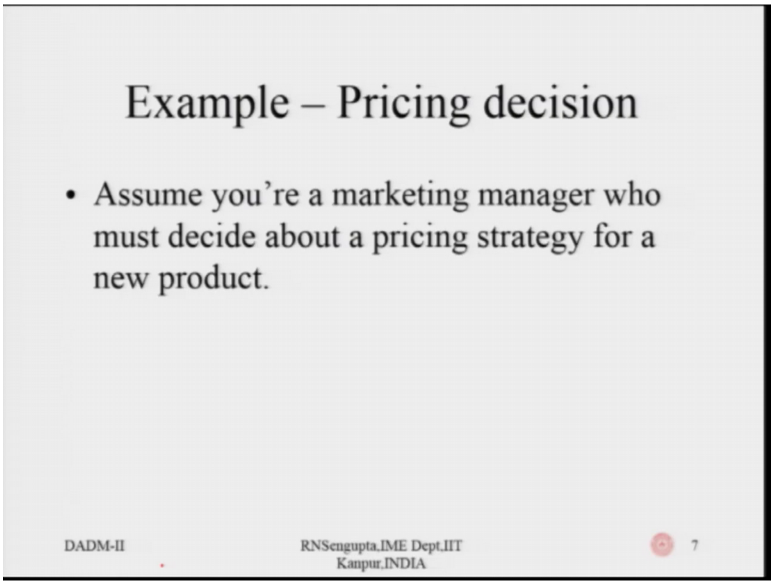

So, let us take this example that you are a marketing manager and you are asked to decide about the optimal pricing strategy for a product that the firm is going to launch.

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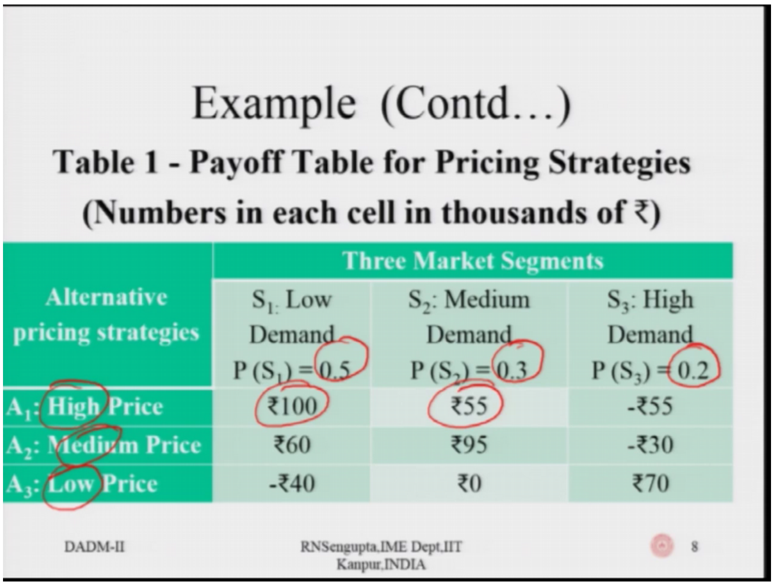

Alternative pricing strategies	Three Market Segments		
	S_1: Low Demand $P(S_1) = 0.5$	S_2: Medium Demand $P(S_2) = 0.3$	S_3: High Demand $P(S_3) = 0.2$
A_1: High Price	₹100	₹55	-₹55
A_2: Medium Price	₹60	₹95	-₹30
A_3: Low Price	-₹40	₹0	₹70

So, to begin with you have a payoff table, suppose there are three segments in the market you choose the that way. You can choose any number of segments in the market, but broadly to make get a simplistic assumption. We take that there are segments with low, moderate demand and high demand and you have three different pricing strategies; so, you have high price, you have medium price and you have low price. And these are the different payoffs which are associated with each of these segments and the pricing strategy. So for and these are the probabilities that there is a 50 percent chance, that there is a low demand for the product, there is a 30 percent chance, that there is a moderate demand and 20 percent chance that there is a high demand for that particular product.

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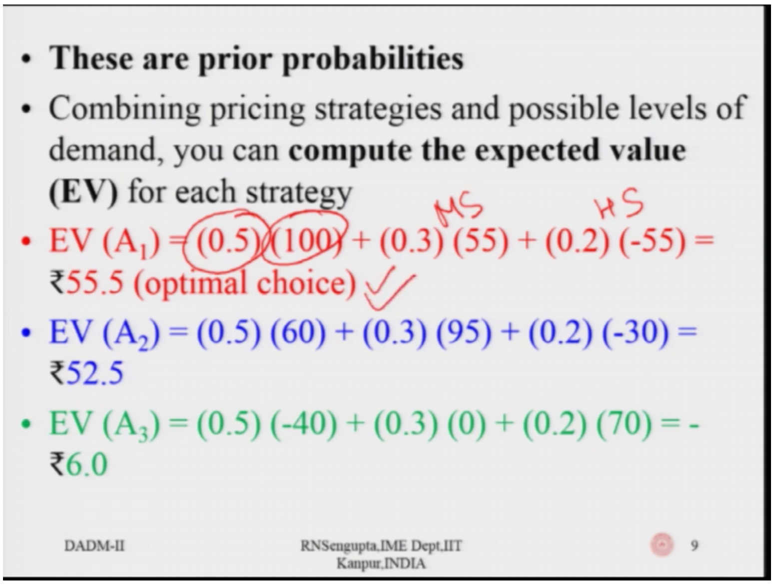

These are all the prior probabilities. So, you do not know exactly how the futuristic market would be once you have launched the product and based on this particular set of information you calculate the expected value. So, expected value as we see here is the probability of the market; for example, this is for low demand and the expected payoff.

Similarly, you do for moderate segments and you do for high demand segments and you calculate the expected values. So, here in this case you see that a pricing policy with low price point is the optimal solution.

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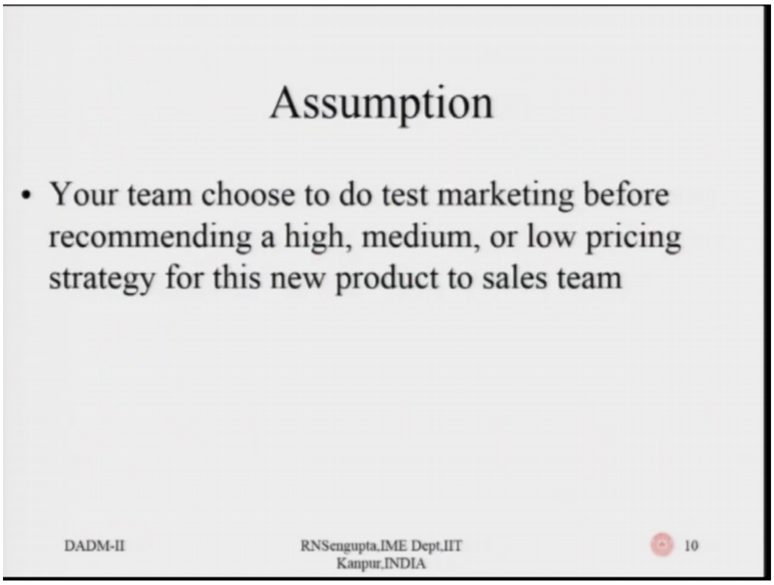

However, your team choose to do a market analysis a test marketing. A test marketing is an activity that a firm adopts to understand the market behaviour wherein you can distribute some free samples, sachet, some coupons. So, that the process, a set of customers can try that product and give you some feedback, whether they are satisfied, they are not satisfied and you take it back that information and make changes in the product or the strategy about that product pricing, features so on and so forth. So you now, do a test marketing based on whatever information you had earlier.

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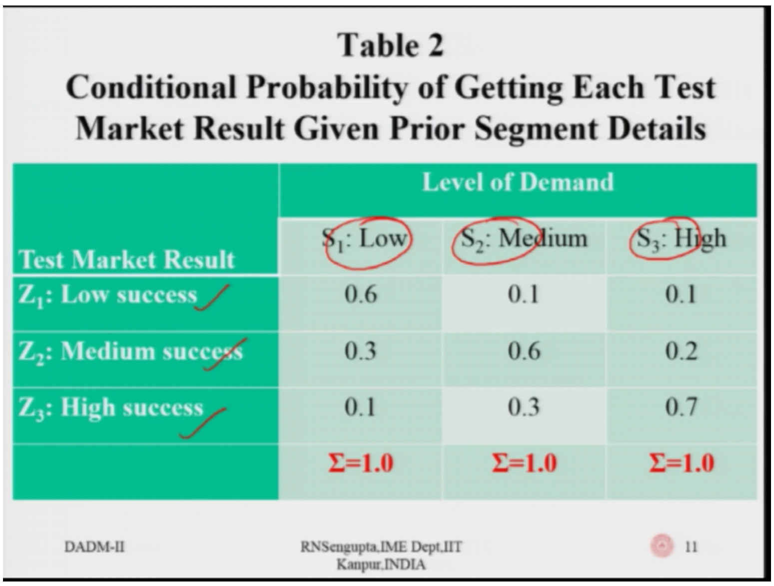

Table 2
Conditional Probability of Getting Each Test Market Result Given Prior Segment Details

Test Market Result	Level of Demand		
	S_1: Low	S_2: Medium	S_3: High
Z_1: Low success	0.6	0.1	0.1
Z_2: Medium success	0.3	0.6	0.2
Z_3: High success	0.1	0.3	0.7
	Σ=1.0	Σ=1.0	Σ=1.0

The test marketing result again can be successful or not successful. So for example, in this case we say that the test market results have low success rate, medium success rate or very high success rate. And we know, what is the level of demand? We have three segments with low demand, medium demand and high demand. And these are the conditional probabilities of getting a particular test result given a certain kind of segment is there. For example, the probability of getting high success test result is 0.1 given that there is a low segment demand.

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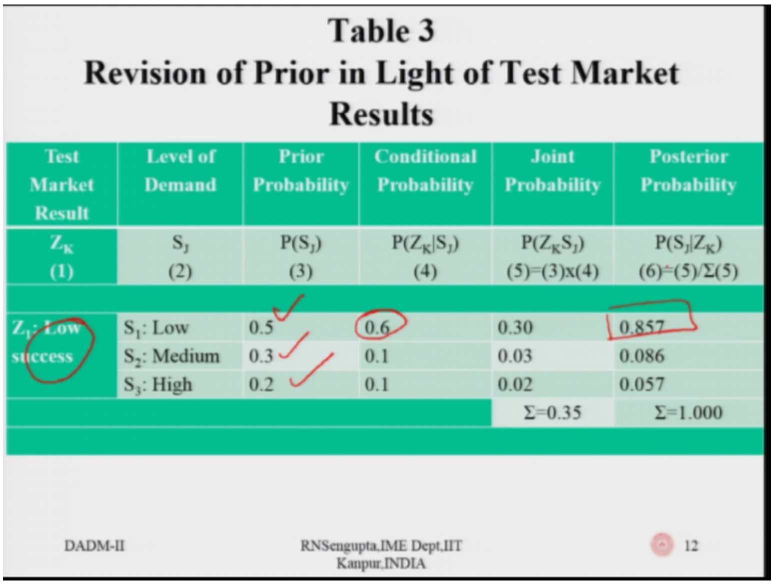

Table 3
Revision of Prior in Light of Test Market Results

Test Market Result	Level of Demand	Prior Probability	Conditional Probability	Joint Probability	Posterior Probability
Z_K (1)	S_J (2)	$P(S_J)$ (3)	$P(Z_K \mid S_J)$ (4)	$P(Z_K S_J)$ (5)=(3)x(4)	$P(S_J \mid Z_K)$ (6)=(5)/Σ(5)
Z_1: Low success	S_1: Low	0.5	0.6	0.30	0.857
	S_2: Medium	0.3	0.1	0.03	0.086
	S_3: High	0.2	0.1	0.02	0.057
				Σ=0.35	Σ=1.000

What you do next is that? You combine the results of test marketing with the prior probabilities that you had for different price points. So, for example, if you have a low success test market result and these are the prior probabilities for different segments, for low medium and high.

You find out the conditional probability which we already had from the previous slide and you find out the posterior probability that what is the probability that the segment is actually a low demand segment given that the test result also showed low success. So, that is how you calculate the posterior probabilities for all the segments given that the test result fall into a certain category of low success, medium success or high success.

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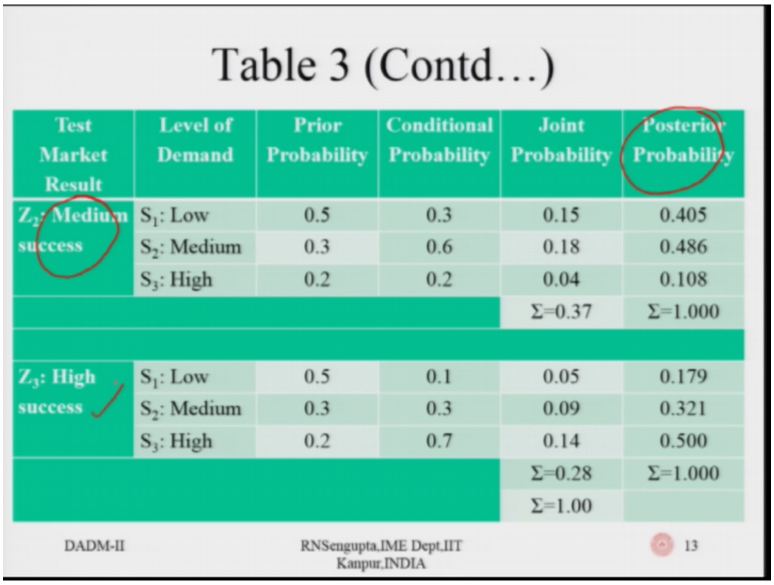

Table 3 (Contd…)

Test Market Result	Level of Demand	Prior Probability	Conditional Probability	Joint Probability	Posterior Probability
Z_2: Medium success	S_1: Low	0.5	0.3	0.15	0.405
	S_2: Medium	0.3	0.6	0.18	0.486
	S_3: High	0.2	0.2	0.04	0.108
				Σ=0.37	Σ=1.000
Z_3: High success	S_1: Low	0.5	0.1	0.05	0.179
	S_2: Medium	0.3	0.3	0.09	0.321
	S_3: High	0.2	0.7	0.14	0.500
				Σ=0.28	Σ=1.000
				Σ=1.00	

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Similarly, you calculate the posterior probability for medium success test result and high success test result.

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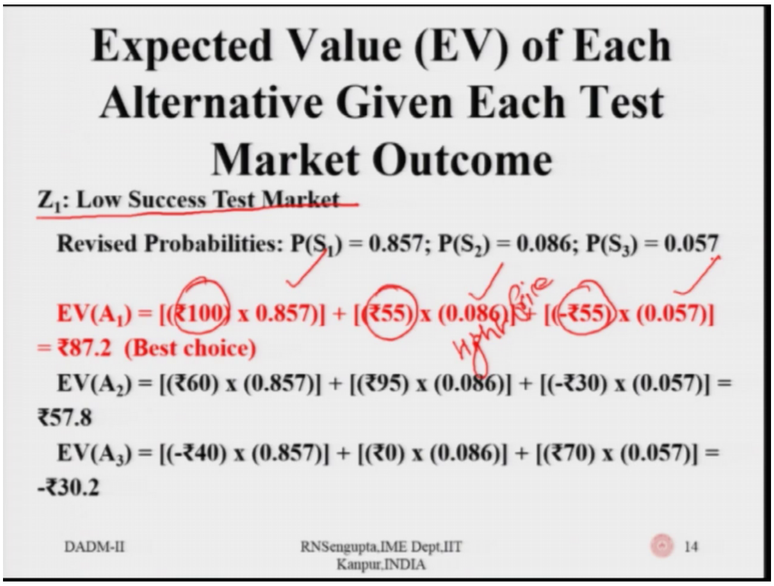

This has to be combined with the payoffs that you expect to get from different pricing policies. And similarly, the way you calculated expected value earlier you again calculate the expected value. But now, you have expected value for three different test market results low medium, high and within those test market results, you will have independent optimal values of the pricing policy.

So for example, we as an we take the low success test market case and expected value we calculate as this is the payoff 100, 55 and minus 55 this is actually for the high price point strategy and this 0.857, 0.086 and 0.057 are the revised or the posterior probabilities after we have taken the test marketing activity. So, in this case when there is a low success rate you find out that the best choice is actually high price point strategy. Similarly, you can calculate for a low moderate test market result and a high test market result and you can modify your actions for that particular product strategy.

So, this is a very simplistic example, how we take into account the prior information to make predictions about the future conditional on certain values or activities or data that we have. So, it combines base rule to with the marketing information to predict the future strategies that the firm should adopt.

Here we had actual probabilities; so, to understand the point we took actual probabilities of how much what is the chance that the market demand is going to be low, medium, high or what is the chance that the market test marketing is going to have low success rate or medium success rate or a high success rate. But in a large number of times we do not have those pointed numbers to be given for these probability distributions.

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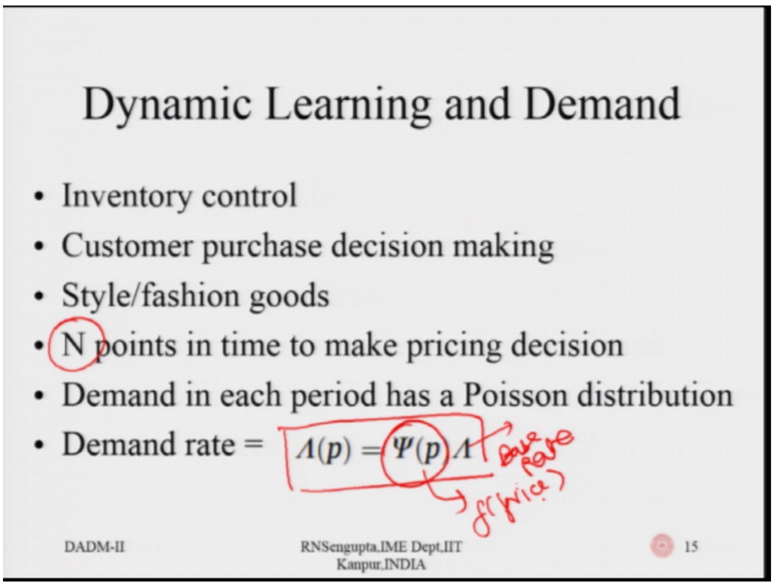

So, what we next look into is something known as dynamic learning demand model, which is very widely used in inventory control and supply chain management and also in understanding customers purchase decision making. For example, in the case of style or fashion goods where the demand is extremely uncertain, we use dynamic learning to launch newer version of fashion goods. So, as we suppose that there are n points in time where you have to make a pricing decision.

So, you are a firm and you have to make a pricing decision for N different points in future and we assume that they are of all unit interval. So, you can say that every year, you want to revise the price and you want to understand how the pricing should be done for say 10 years or 15 years from now. So, we assume that the demand in each period has a Poisson distribution, where the demand rate lambda is given by psi p into lambda where this is something known as the base rate and this factor psi is actually a function of price.

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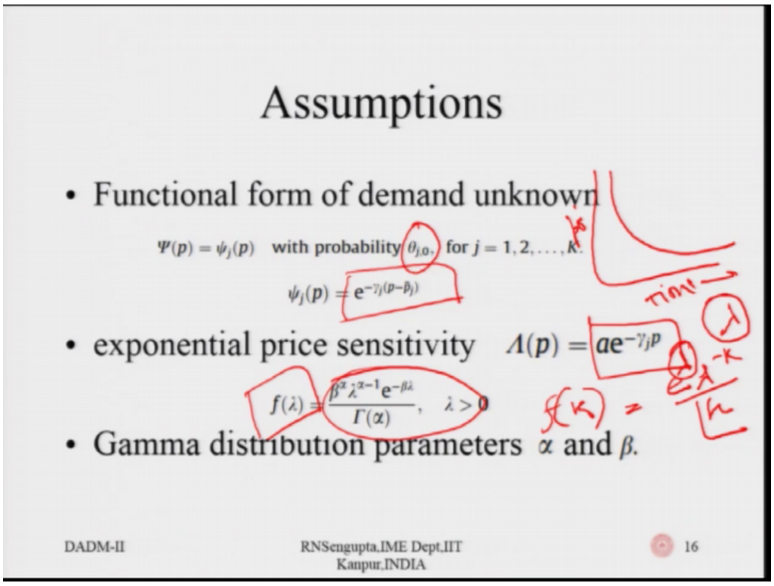

Now, the functional form of demand is unknown; so, we do not know exactly what is the firm in which the demand is going to be. So, we assume that psi p can take any of the k form; k functional forms starting from 1 to k, each has a certain probability of occurrence which is given by say theta j comma 0 and we say that, this psi is again an exponential function of price.

Exponential function of price or the exponential price sensitivity is widely applied in marketing applications, if you see specially in the high tech sector or in say any of these electronics market, you will see that the price decreases exponentially over time. So, and there is something known as price quality heuristic; so higher the price initially, you will find that there is an increase in the sales and slowly it goes down. So, it the prices follow like this if this is price and this is time so, it goes like this.

So now, we have this exponential price sensitivity and because we and we assume that the intensity of customer arrival is taken as a Poisson distribution. So from the nature of that distribution, we can say that the dance density function of customer arrival will be given by this equation. So, for Poisson process for say k occurrences of any event, you have e to the power and suppose lambda is the mean rate of occurrence.

So, in f k is traditionally given by this equation and here in this case for us this lambda is the customer arrival rate. So, we plug in those in those details to find out what is the density function of lambda. Now, we assume that lambda follows a gamma distribution with the parameters, alpha and beta, where alpha is the scale and beta is the shape parameter.

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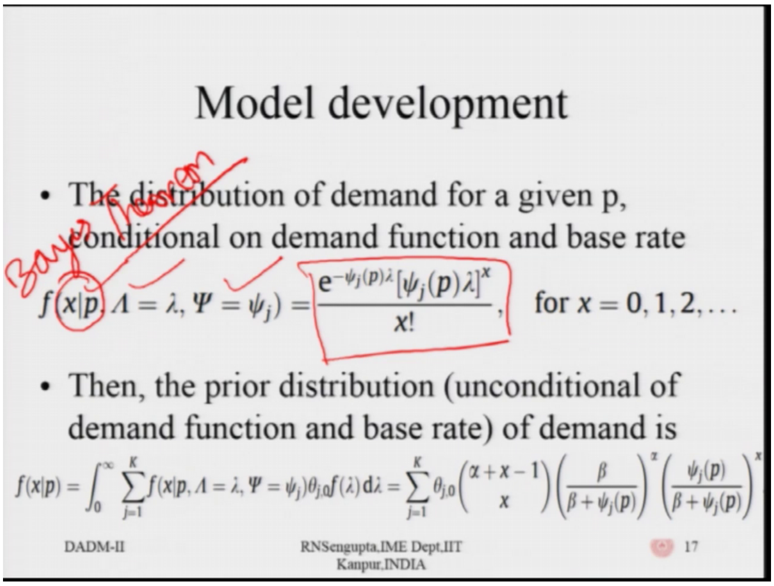

So, finally, the distribution of demand for a given price, p conditional on demand function and the base rate. So, here comes the application of the base theorem. So, where we say that, we are trying to find out what is the demand, we know the price, we know that what is the distribution of lambda which is the intensity of customer arrival and we also know that there are different k functions functional forms that the demand function can take.

So, based on that we come up with this distribution of demand for a given price point base rate and the demand function. And we calculate the posterior distribution of the demand based on the base rule.

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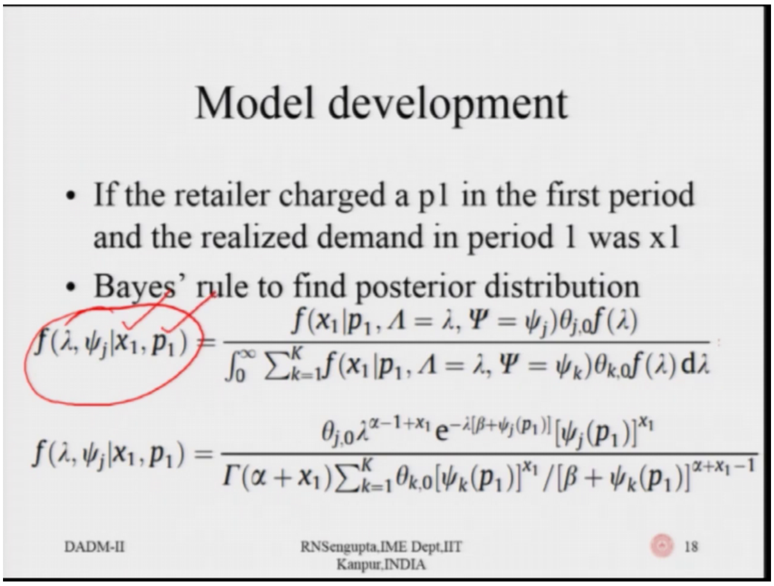

So, if the retailer charges the price p 1 in the first period and realized demand in period 1 was x 1, then we can find out the posterior distribution for lambda contingent on these values x 1 and p 1.

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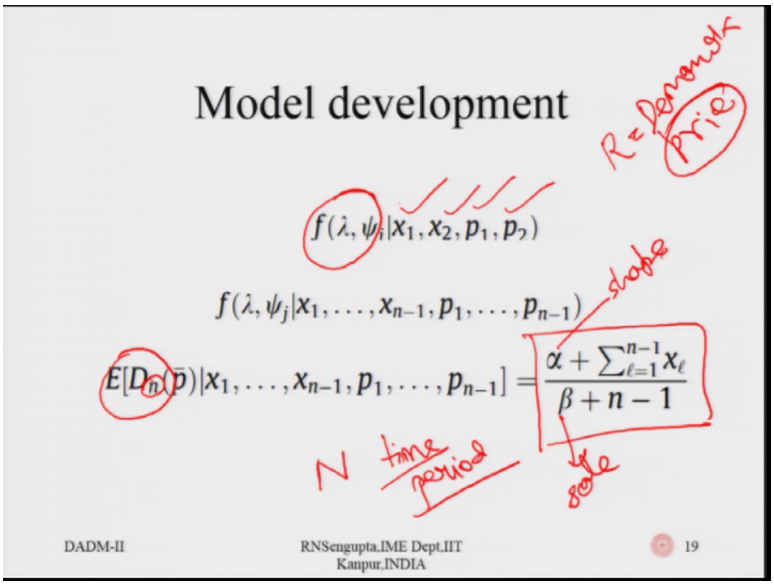

And similarly, if we know the prior sales and the price for 2 periods say x 1 and x 2, p 1 and p 2 we can find out the posterior distribution based on those values. And the if you solve it further the expected demand at some point n because, we understood there are n time periods to make a pricing decision. So, we can take that demand at some point n is actually given by this particular function where alpha is the shape and beta is the scale parameter of the gamma distribution.

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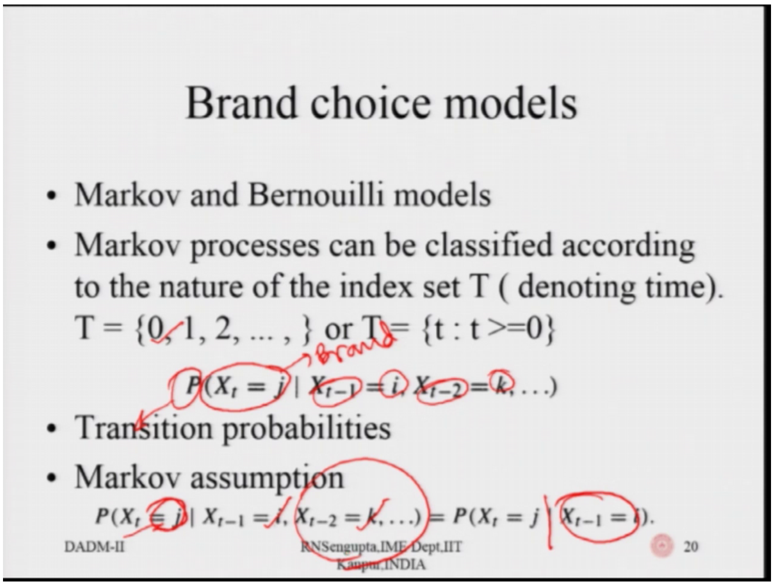

So, that was 1 way that was you have the expected demand you can actually calculate the revenue; expected revenue; so, the revenue would be demand multiplied by the price point. And you can actually see how the revenues are revenues are changing over a period of time because prices again a function of time over here and the objective function for the firm would be to maximize the revenues and find out the price at which the revenue is maximum. So, the idea in this particular example is that contingent we first of all we feel that the demand is something that is contingent on the price, price is something that firm has to decide.

Now, how will the firm decide the price? It will observe the demand, it will make predictions about the demand for certain period of time and then it will try to maximize the revenue considering that ok. These is the predicted set of demand for say 10 years to come, this is how I want to maximize my revenue and what should be the price point to do that because, there are also cost associated with it there are cost of development there are cost of commercialization, marketing and advertising. So, that will form as one of the constraints or budgets that the firm has.

So, next we move to another set of models which is known as brand choice models which have very widely utilized in marketing literature and marketing application this is based on Markov and Bernouilli models. So, basically if there are more than one brands in the market for example, Pepsi, Coke, Miranda then how do you judge which brand is going to be preferred by one consumer; a segment of consumer because that will help you to plan your marketing strategy. So, that you become the preferred brand choice by those set of consumers because it is linked to your revenues and market share.

So, it is very important for a firm to understand the preferences of the customers because it can modify their of its offerings or it can use marketing to influence the decision making of those customers. So, Markov process can be classified according to say nature of the index for example, in our case we take T. T is for time and we have time period starting from 0 to infinite it is greater than equal to 0.

So, the probability that a person has purchased brand j at some point t conditional on the fact that he purchased brand i at t minus 1, brand k at t minus 2, this is given as the conditional probability of current purchases based on past purchases given that you have a set of brands available in the market. This these are called as transition probabilities, this P is known as the transition probability; why transition? Because you may have purchased a different brand in the previous time period and now you are going to a different brand as the purchase decision choice.

When we say a Markov process there is an hidden assumption that the probability that you are going to purchase branch j given that you purchase i, k so on and so forth in all previous time periods is dependent only on X t minus 1 equal to i basically, it is only contingent on what was the prior purchase. So, we are not looking into X t minus 2, t minus 3, t minus 4 time periods, we are just looking into what was the last purchase decision.

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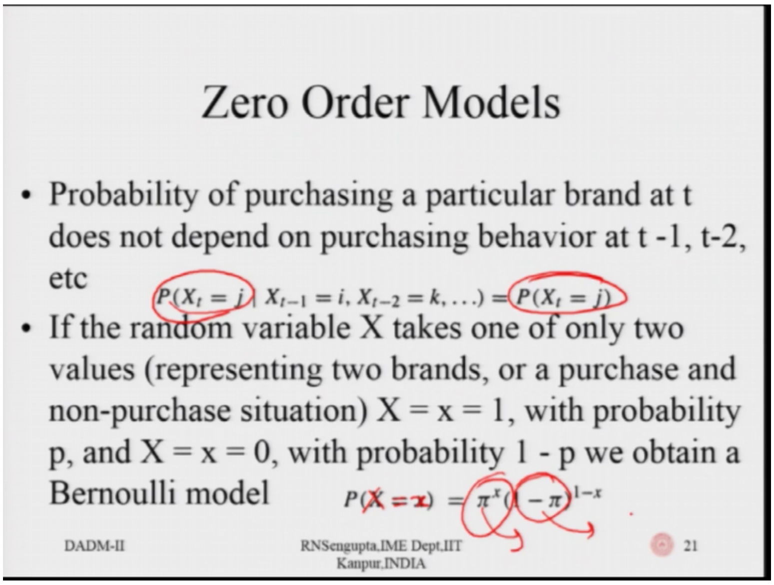

So, there are a zero order, there are first order, there are n'th order Markov models, we will first discuss the zero order model and then we go to the first order model and we will wrap it up with that discussion. So in zero order model, what we say is that we the present purchase decision does not depend on any of the past purchase decisions. So, for here we when we discussed we said that Markov assumption is that probability of purchasing j given that we purchased i in the prior time period we do not make that assumption in the zero order. Zero means that it the car it is all independent choices at different time period.

So, probability that you purchase brand j at a given time is actually you just purchased brand j, it does not matter what you have purchased in the prior time period. So, if the random variable x takes one of only two values suppose there are only two brands; so, either you will purchase that brand or you will not purchase that branch. So, and you have the probabilities p and 1 minus p of purchase and on purchase or pi and 1 minus p or a pi of purchase and on purchase. So, it becomes actually a Bernoulli distribution where is the probability of X equal to x is that this is the purchasing probability and this is the non-purchasing probability.

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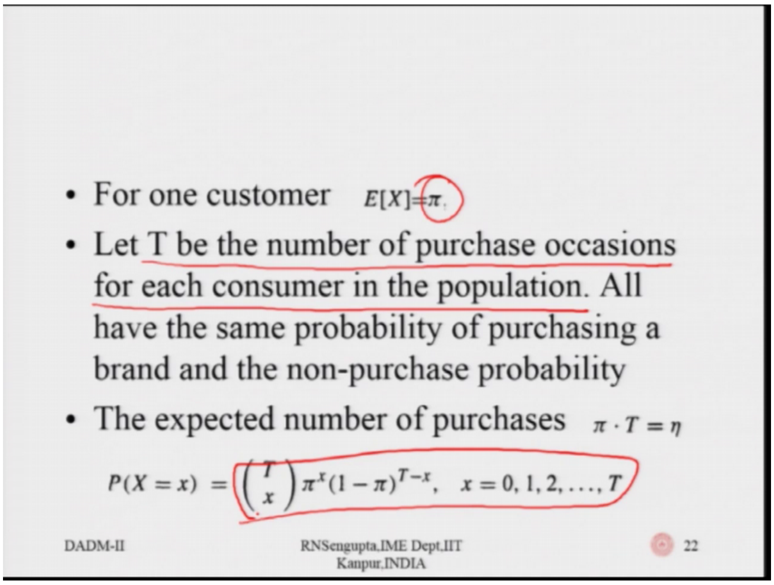

So, for one customer we can say the expectation of purchasing X is given by pi which is the purchasing probability. And if there are T number of purchase occasions for each customer in the population, we assume that all have the same purchasing or non-purchasing probability, then the expected number of purchases would be given by this equation.

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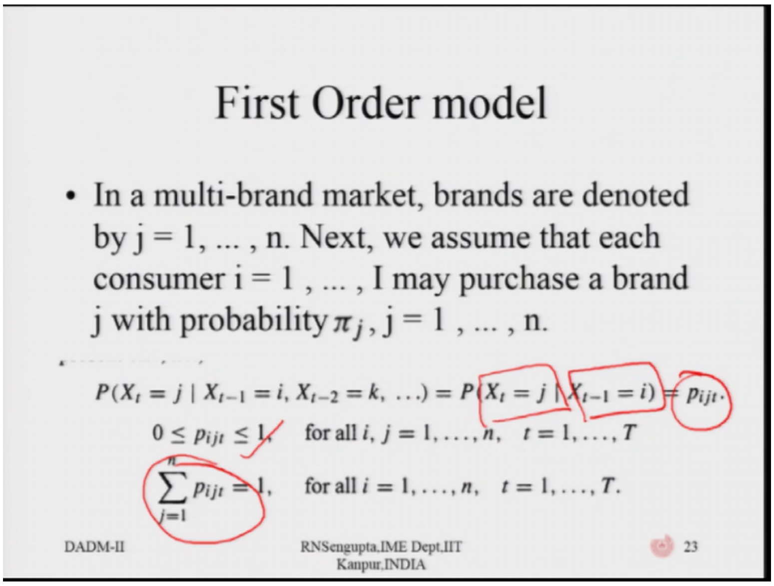

Now, we come to the first order model. In first order model what we assume that each consumer i, may purchase a brand j with certain probability pi j and this purchase decision is based only on one period prior purchase decision. So, X t equal to j is given X t minus 1 equal to i. So, in if in the if last year I purchase say, Samsung then, what is the purchase a probability of purchasing Philips in this year and that is what is pijt.

We say that pijt is between 0 and 1 because it is a probability and the sum of all such transition probabilities is equal to 1. So, this is what is the difference between 0 order and first order. When we talk about nth order then my purchase decision as of today but depend on last end purchase behaviours. So, that will make it make the distinction between first order or nth order.

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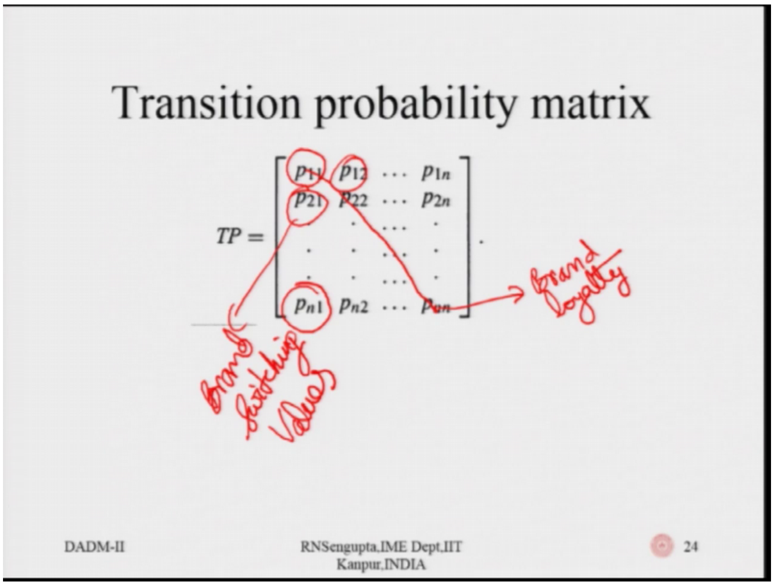

Now, this is the transition probability. So, this is purchasing brand 1, in last time period as well as in this time period. These are all the diagonal elements are important for the form because they talk about something known as brand loyalty, because the customer continues to buy the same brand in different time periods. And these are the brand switching values because you bought brand 1 in the last time period and now you are shifting to brand 2, last time you brought bought brand 1 and now you are shifting to nth brand. So, this is known as transition probability matrix for n different brands which are there in the market.

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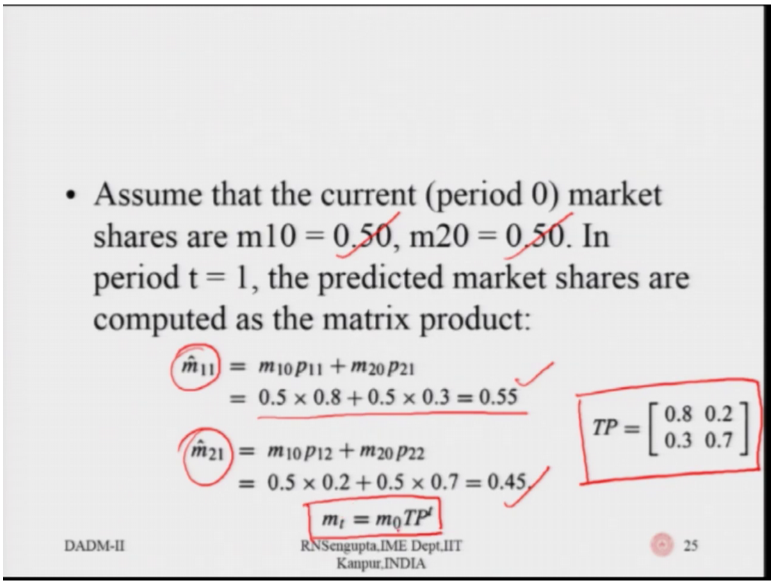

So, in terms of numbers to understand how it is utilized in decision making, we assume that the current period market share of different brands is say 0.5, 0.5 and there are 2 brands in the market say for example, Pepsi and Coke. So, in period t equal to 1, the predicted market share which can be computed as per this. So, this is the transition probability matrix that the loyalty factor that there is an 80 percent chance that the consumer will again repeat brand 1, there is a 70 percent chance that the consumer will again repeat brand 2

So, in the next time period market share of 1 given that they he bought (Refer Time: 24:45) brand 1 and market share of 2 given that he bought brand 1 is given by this equation. So, the next period brand share for different brands would be 0.55 and 0.45, you can see that this add up to 1 because the total market share we assume is 1 constant. So, over a long period of time when we say that is steady state has reached. So, to calculate market share at some time t, you can use this formula that initial market share multiplied by the transition probability till that particular time.

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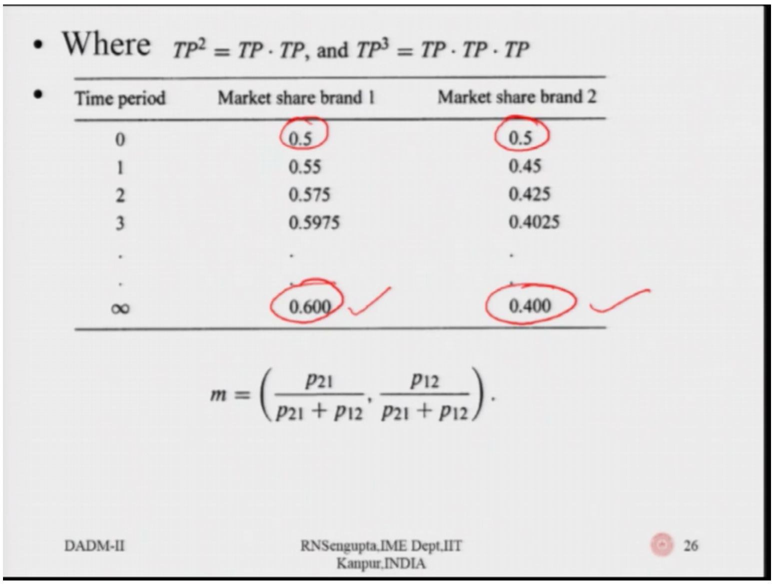

So, TP 2 will be transition probability twice and TP 3 will be transition probability into 3. So, if you calculate this over time, you will find that the steady state market shares for brand 1 and brand 2 are 0.6 and 0.4. So, we started that they were equal in terms of market share, but over a period of time the market share of brand 1 has increased. So, if depending on which brand are you are you in brand 1 or are you in brand 2 category, you will have to adopt a different advertising and marketing strategy to influence customers that you retain the market share for sustained growth and profitability.

Another formula that you can utilize to calculate this steady state market share is probability 2 1 divided by probability of 2 1 plus probability of 1 2 and this so. These probabilities are nothing but the transition probability that, how you are going to switch. So, the probability that the person purchase brand 2 given that he purchase brand 1 in the trial period divided by what is the probability that he purchase brand 2. Now, conditional or brand 1 in the prior period plus the probability that he will purchase 1, conditional on probability of purchasing brand 2 in the prior time period. So, this is another formula that you can use.

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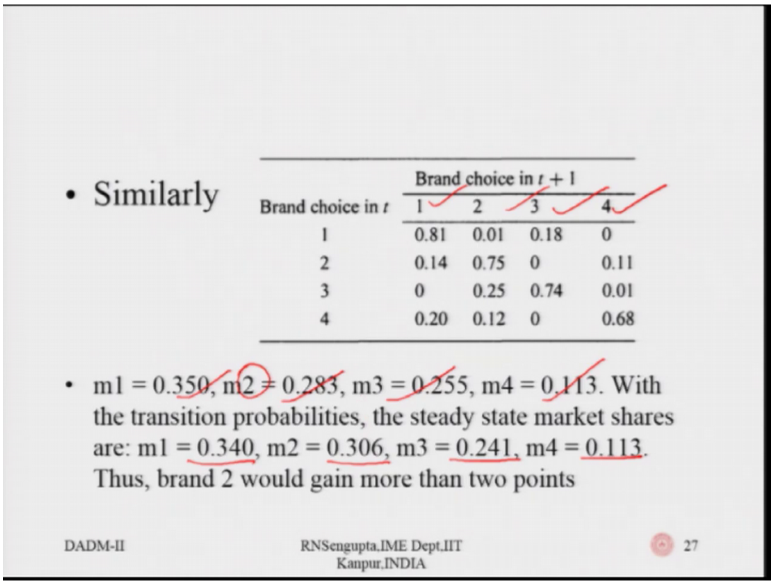

Similarly, that if you have 4 brands in the market you do a similar analysis, the way we did for the 2 brand a market in earlier case and you can say that, just if you start with these market shares in time t equal to 0 and you calculate you will find that the steady state market shares are these. So, what it means is that m 2 brand 2 has actually increased the market share and brand 3 and brand 1 have actually lost the market share. So, that is how these models are used by firms to make strategy decisions in terms of advertising and.

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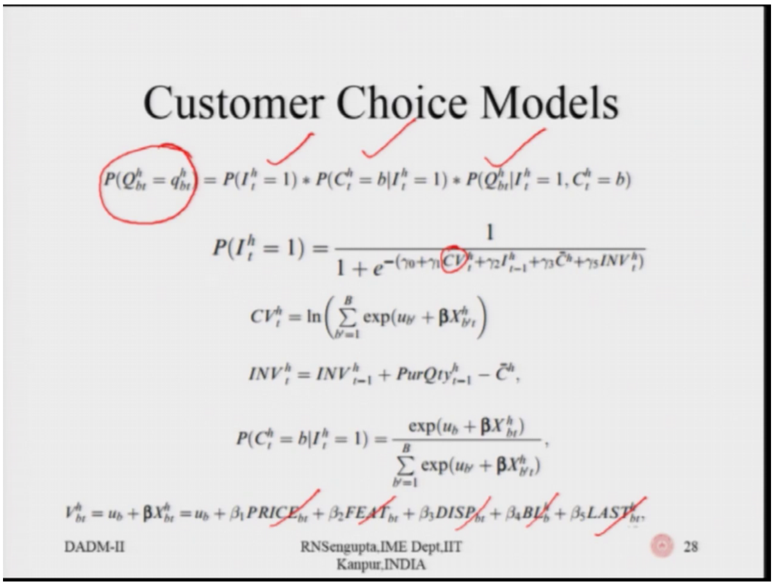

Now, I will wrap it up very quickly with 1 more consumer choice model wherein we talk about purchase incidence, we talk about purchasing a category of brand b and the quantity that you purchase in that particular category which actually forms the purchase behaviour of that particular household for that brand b. In a shopping trip p and this is given using the utility theory where the CV which is the a value that the consumer associates with buying a particular brand comes from different factors. For example, the price, the feature, the display, the brand loyalty and the factor that what he or she purchased last time because that decides the satisfaction level of that particular customer.

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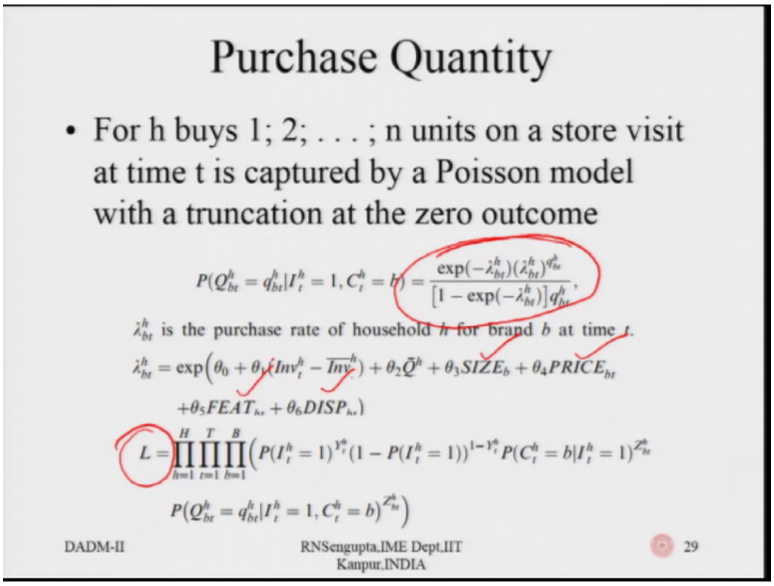

So, once you know what is the quantity that in the consumer purchased beyond a store visit and we assume that the store visit time t, he by say n units and it is captured as a Poisson model. Then you can calculate what is the purchases rate for that particular brand? And you can use the maximum likelihood estimation to understand what could be the different parameters at which parameters for size, for price, for display, for features that actually affect the brand choice of that particular consumer and accordingly you can modify your factors.

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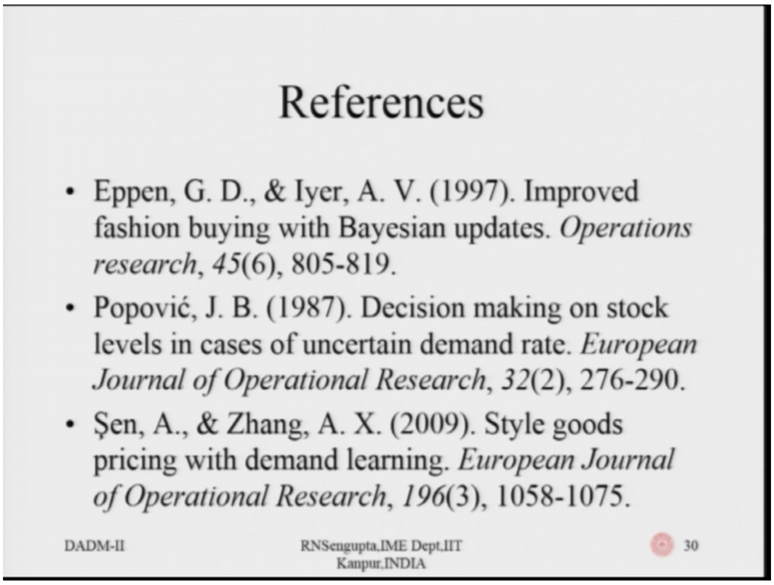

These are some of the top references that you can treat to in increase your understanding in this particular area of brand choice models and consumer decision making models and. I hope that this could add some value to your learnings from this particular course and you could understand how these quantitative models are actually used by a firm in making strategic decisions for the product launch or for maintaining sustained revenues for a period of time.

Thank you.