

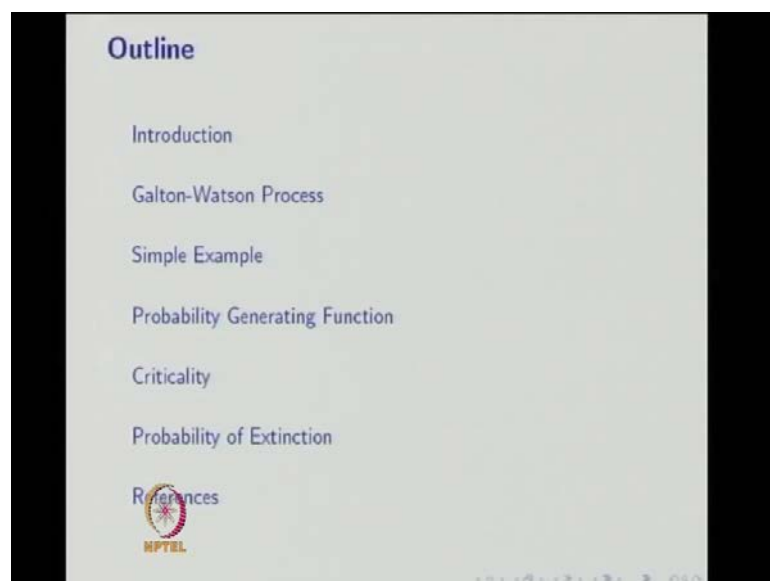
Stochastic Processes
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Module - 9
Branching Processes
Lecture - 1
Galton-Watson Process

This is stochastic processes, module nine, branching processes. In the module one we have discussed review of probability; module two, we have introduced stochastic process; module three, we have discussed stationary processes; module four, we have discussed discrete time Markov chain; module five, we have discussed continuous time Markov chain; module six, we have discussed the martingale; module seven; we have discussed about Brownian motion or wiener process; module eight, we have discussed renewal process.

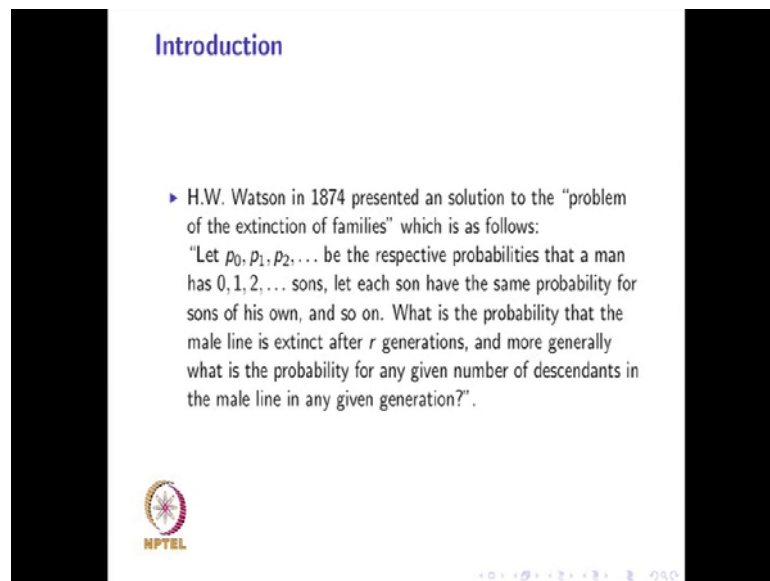
In this module we are going to discuss the branching processes. It covers two lectures, in these two lectures we are going to cover the definition and examples of branching processes. Two important branching processes, Galton-Watson branching process and that Markov branching process are going to be discussed. Important measures like perform probability of extinction, limit theorem, limit distribution and mean of branching process will be discussed.

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In the lecture 1 we are going to start with the introduction to branching processes, followed by that we are going to start the Galton-Watson process, few examples will be discussed. Then, we are going to discuss the probability generating function of Galton-Watson branching process. Then, we are going to discuss the criticality and probability of extinction.

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The slide is titled "Introduction" in blue text. It contains a bullet point starting with a blue triangle, followed by text describing H.W. Watson's 1874 work on the extinction of families. The text includes a quote about probabilities p_0, p_1, p_2, \dots and asks for the probability of extinction after r generations. At the bottom left is the NPTEL logo, and at the bottom right are navigation icons.

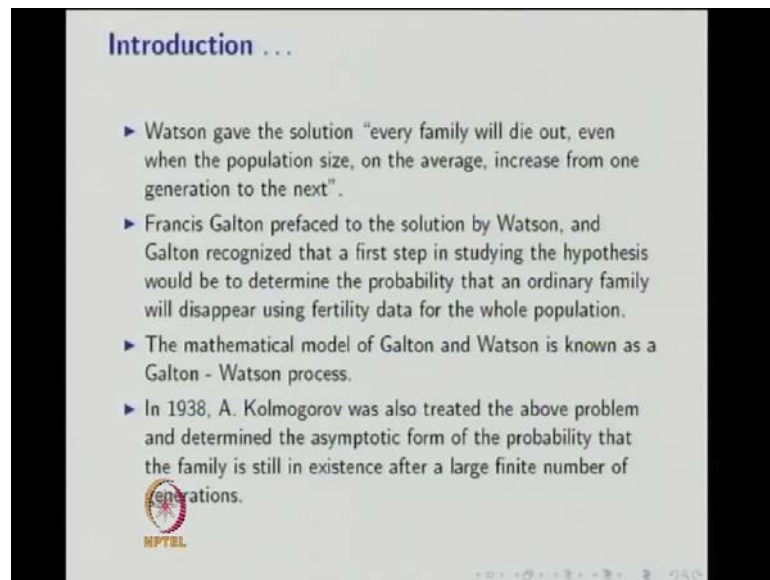
Introduction

- ▶ H.W. Watson in 1874 presented an solution to the "problem of the extinction of families" which is as follows:
"Let p_0, p_1, p_2, \dots be the respective probabilities that a man has 0, 1, 2, ... sons, let each son have the same probability for sons of his own, and so on. What is the probability that the male line is extinct after r generations, and more generally what is the probability for any given number of descendants in the male line in any given generation?"

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Watson in 1974 presented a solution to the problem of extinction of families, which is as follows. Let p_0, p_1, p_2 be the respective probabilities, that the man has 0, 1, 2 and so on, sons. Let each son have the same probability for sons of his own and so on. What is the probability, that the male line is extinct after r generations and more generally, what is the probability for any given number of descendants in the male line in any given generation?

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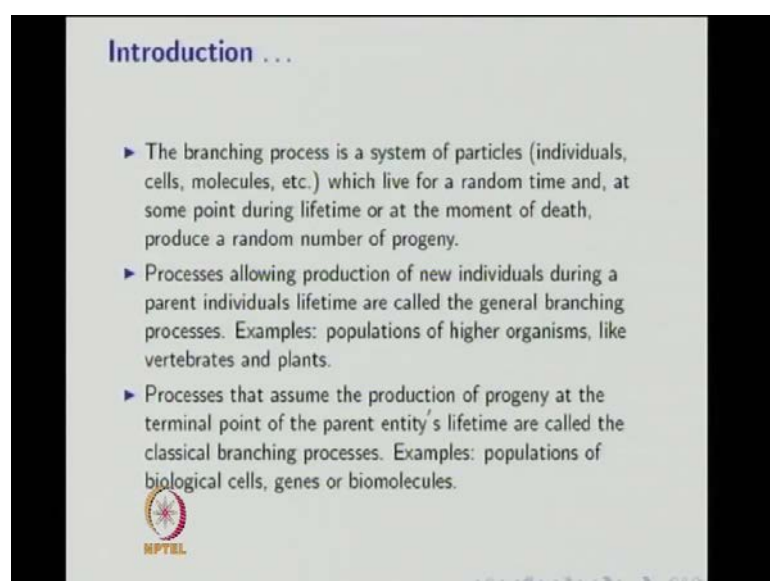
Introduction ...

- ▶ Watson gave the solution "every family will die out, even when the population size, on the average, increase from one generation to the next".
- ▶ Francis Galton prefaced to the solution by Watson, and Galton recognized that a first step in studying the hypothesis would be to determine the probability that an ordinary family will disappear using fertility data for the whole population.
- ▶ The mathematical model of Galton and Watson is known as a Galton - Watson process.
- ▶ In 1938, A. Kolmogorov was also treated the above problem and determined the asymptotic form of the probability that the family is still in existence after a large finite number of generations.

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Watson gave the solution, every family will die out, even when the population size, on the average, increase from one generation to the next. Galton prefaced to the solution by Watson and Galton recognized that the first step in studying the hypothesis would be to determine the probability, that the ordinary family will disappear using fertility data for the whole population. The mathematical model of Galton and Watson is known as a Galton-Watson branching process. In 1938, Kolmogorov was also treated the above problem and determined the asymptotic form of the probability, that the family is still in existence after a large finite number of generations.

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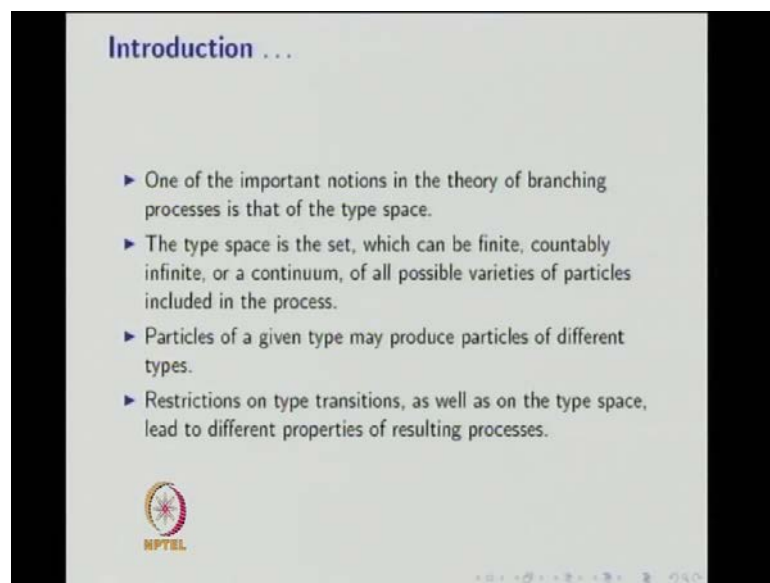
Introduction ...

- ▶ The branching process is a system of particles (individuals, cells, molecules, etc.) which live for a random time and, at some point during lifetime or at the moment of death, produce a random number of progeny.
- ▶ Processes allowing production of new individuals during a parent individuals lifetime are called the general branching processes. Examples: populations of higher organisms, like vertebrates and plants.
- ▶ Processes that assume the production of progeny at the terminal point of the parent entity's lifetime are called the classical branching processes. Examples: populations of biological cells, genes or biomolecules.

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The branching process is a system of particles or individuals or cells or molecules, which live for a random time and, at some point during lifetime or at the moment of death, produce a, random number of progeny, random number of progeny. Processes allowing production of new individuals during a parent individual's lifetime are called the general branching processes. Examples: populations of higher organisms like vertebrates and plants. Processes that assume production of progeny at the terminal point of the parent entity's lifetime are called the classical branching processes. Examples: population of biological cells, genes or biomolecules.

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One of the important notation; one of the important notions in the theory of branching processes is that of the type space. The type space is the set, which can be finite, countably infinite or continuum, of all possible varieties of particles including in the process. Particles of a given type may produce particles of different types. Restrictions on the type transitions, as well as on the type space, lead to different properties of resulting processes.

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Classical Branching Process

- ▶ Consider a classical branching process in which progeny are born at the moment of the parents death.
- ▶ The distribution of particle lifetime τ has much impact on the behavior and analysis of the process.
- ▶ If $\tau = 1$, then it is called the Galton - Watson process.
- ▶ If τ is exponentially distributed random variable, then the resulting process is called a Markov branching process.
- ▶ If τ is an arbitrary non-negative random variable, the resulting process is called an "age-dependent" or Bellman - Harris process.




Now, we are going to discuss the classical branching processes. Consider a classical branching process in which progeny are born at the moment of parent's death. The distribution of particle lifetime τ has much impact on the behavior and analysis of the, of the price, of the process. If τ is equal to 1, then it is called Galton-Watson process. If τ is exponentially distributed random variable, then the resulting process is called Markov branching process. In this model we are going to discuss in detail Galton-Watson process and Markov branching process. If τ is arbitrary non-negative random variable, the resulting process is called age-dependent or Bellman-Harris process.

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Galton-Watson Process

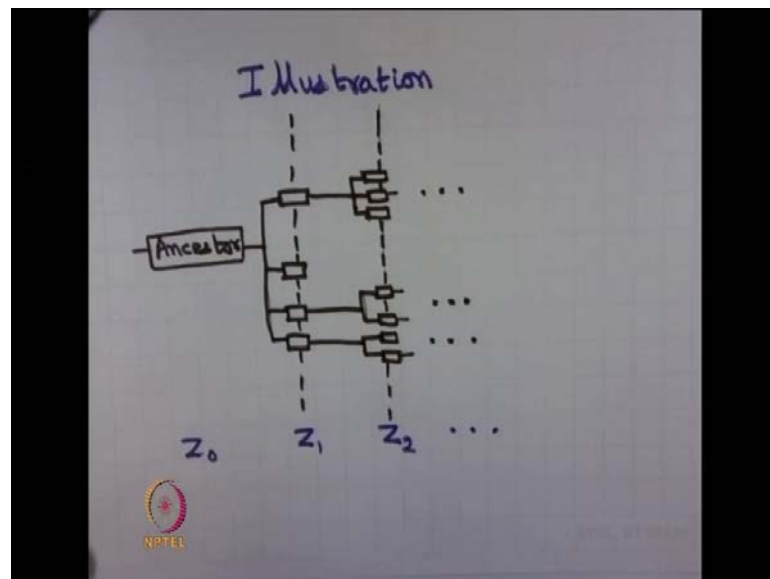
- ▶ Consider particles that can generate additional particles of the same kind.
- ▶ An initial set of particles, which we call the 0-th generation, have offspring that are called the first generation, their offspring are the second generation, and so on.
- ▶ We denote by Z_0, Z_1, Z_2, \dots as the number of particles in the 0-th, 1-th, 2-nd, ... generations.
- ▶ Furthermore, we make the following assumptions:
- ▶ If the size of the n -th generation is known, then the probability law governing later generations does not depend on the sizes of generations preceding the n -th.

It means $\{Z_n, n = 0, 1, \dots\}$ is a discrete time Markov chain.



Now, we are going to discuss Galton-Watson process. In the next lecture, lecture 2, we are going to discuss Markov branching process. Consider particles, that generate, that can generate additional particles of the same kind. An initial set of particles, which we call the 0th generation having offspring, that are called 1st generation, their offsprings are the 2nd generation and so on. We denote by Z_0, Z_1, Z_2 , as the number of particles in the 0th, 1st, 2nd generations. We see the illustration, this is Z_0, Z_1, Z_2 and so on.

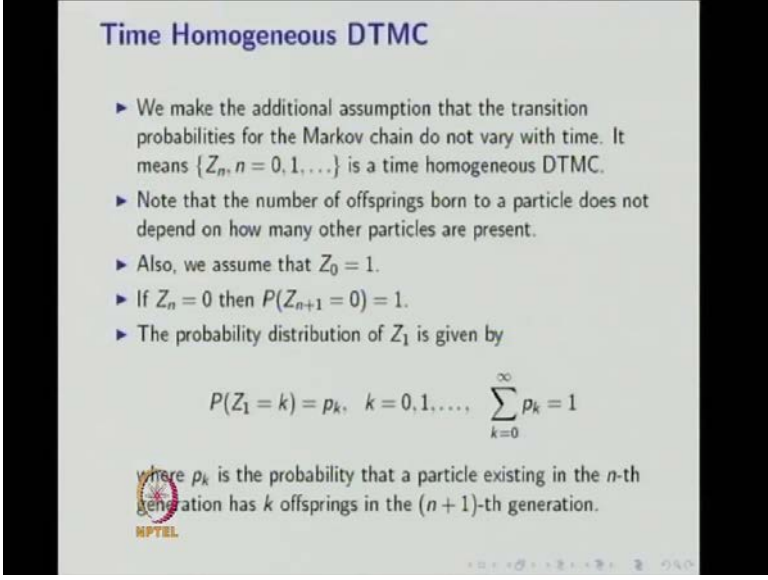
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So, this is the illustration of the number of particles in the 1st generation, 0th generation, 1st generation, 2nd generation and so on.

Furthermore, we make the following assumptions. If the size of the n th generation is known, then the probability law governing later generations does not depend on the sizes of generations preceding the n th. It means the sequence of random variables Z_n form a discrete time Markov chain.

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Time Homogeneous DTMC

- ▶ We make the additional assumption that the transition probabilities for the Markov chain do not vary with time. It means $\{Z_n, n = 0, 1, \dots\}$ is a time homogeneous DTMC.
- ▶ Note that the number of offsprings born to a particle does not depend on how many other particles are present.
- ▶ Also, we assume that $Z_0 = 1$.
- ▶ If $Z_n = 0$ then $P(Z_{n+1} = 0) = 1$.
- ▶ The probability distribution of Z_1 is given by

$$P(Z_1 = k) = p_k, \quad k = 0, 1, \dots, \quad \sum_{k=0}^{\infty} p_k = 1$$

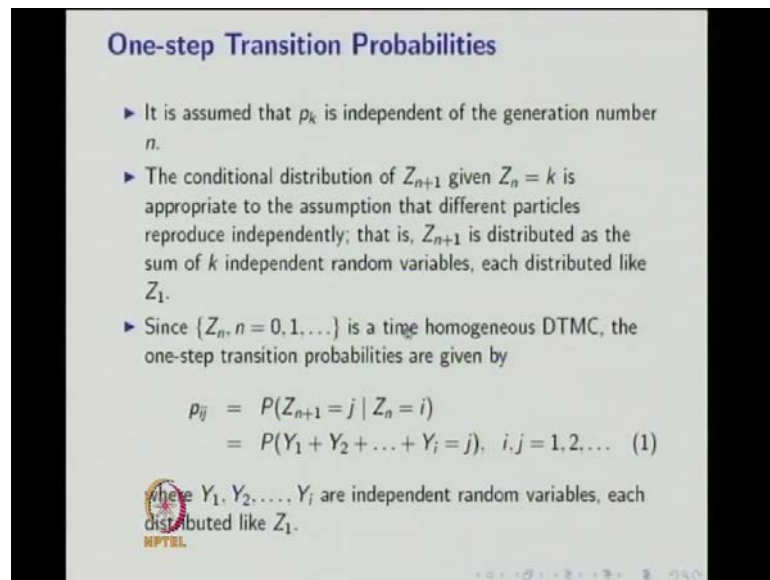
where p_k is the probability that a particle existing in the n -th generation has k offsprings in the $(n+1)$ -th generation.

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We make additional assumption that the transition probabilities for the Markov chain do not vary with time. It means, the sequence of random variables Z_n is a time homogenous discrete time Markov chain. We have discussed the discrete time Markov chain in the module 4 in detail. Note that the number of offspring's born to a particle does not depend on how many other particles are present.

Also, we assume, that Z_0 is equal to 1. In the illustration also we made it Z_0 is equal to 1. Z_1 is a random number of particles; Z_2 is a random number of particles and so on. If Z_n is equal to 0, then the probability of Z_{n+1} is equal to 0 is equal to 1. The probability distribution of Z_1 is given by the probability of Z_1 takes a value k , that is nothing but in notation p_k and the summation of p_k is equal to 1, where p_k is the probability, that a particle existing in the n th generation has k offsprings in the $n+1$ th generation. So, this is the probability mass function for the random variable Z_1 .

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One-step Transition Probabilities

- ▶ It is assumed that p_k is independent of the generation number n .
- ▶ The conditional distribution of Z_{n+1} given $Z_n = k$ is appropriate to the assumption that different particles reproduce independently; that is, Z_{n+1} is distributed as the sum of k independent random variables, each distributed like Z_1 .
- ▶ Since $\{Z_n, n = 0, 1, \dots\}$ is a time homogeneous DTMC, the one-step transition probabilities are given by

$$\begin{aligned} p_{ij} &= P(Z_{n+1} = j \mid Z_n = i) \\ &= P(Y_1 + Y_2 + \dots + Y_i = j), \quad i, j = 1, 2, \dots \quad (1) \end{aligned}$$

where Y_1, Y_2, \dots, Y_i are independent random variables, each distributed like Z_1 .

NPTL


It is assumed, that p_k is independent of the generation number n . The conditional distribution of Z_{n+1} given $Z_n = k$, is appropriate to the assumption, that the different particles are reproduce independent, that is Z_{n+1} is distributed as the sum of k independent random variables, each distributed like Z_1 .

Since the sequence of random variables Z_n is a time homogenous discrete time Markov chain, the one step transition probabilities are given by p_{ij} that is nothing but the probability, that Z_{n+1} is equal to j , given Z_n is equal to i , that is same as Y_1 plus Y_2 , plus, and so on plus Y_i , that takes a value j for (i, j) belonging to $1, 2$ and so on, where Y_i 's are i.i.d. random variables, each distributed like Z_1 . So, the illustration for the Galton-Watson process is Z_0 is equal to 1, Z_1 here it is 4 and Z_2 is 7 and so on.

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Example 1.

- ▶ Consider the Galton - Watson process $\{Z_n, n = 0, 1, 2, \dots\}$ with offspring distribution $\{p_k\}$.
- ▶ Assume that $p_0 = 1/5, p_1 = 3/5$ and $p_2 = 1/5$.
- ▶ Calculate $P(Z_2 = 3 \mid Z_1 = 2)$, $P(Z_3 = 2 \mid Z_2 = 3)$ and $P(Z_2 = 2)$.
- ▶ $P(Z_2 = 3 \mid Z_1 = 2)$

$$\begin{aligned}
 &= P(Y_1 + Y_2 = 3) \\
 &= P(Y_1 = 0, Y_2 = 3) + P(Y_1 = 1, Y_2 = 2) \\
 &\quad + P(Y_1 = 2, Y_2 = 1) + P(Y_1 = 3, Y_2 = 0) \\
 &= P(Y_1 = 0)P(Y_2 = 3) + P(Y_1 = 1)P(Y_2 = 2) \\
 &\quad + P(Y_1 = 2)P(Y_2 = 1) + P(Y_1 = 3)P(Y_2 = 0) \\
 &= p_0 p_3 + p_1 p_2 + p_2 p_1 + p_3 p_0 \\
 &= 0 + \frac{3}{25} + \frac{3}{25} + 0 = \frac{6}{25}
 \end{aligned}$$


Now, let us consider a simple example. Consider the Galton-Watson process Z_n with offspring distribution p_k . Assume, that p_0 is equal to 1 by 5, p_1 is equal to 3 by 5 and p_2 equal to 1 by 5. So, this is the probability mass function for the random variable Z_1 . Our interest is to find out the conditional probability p . Probability of Z_2 is equal to 3, given Z_1 was 2 and also probability, that Z_2 is equal to 2, given Z_1 was 3 and also, probability of Z_2 is equal to 2. So, the conditional probability p Z_2 is equal to 3 given Z_1 is equal to 2, that is same as probability of Y_1 plus Y_2 equal to 3. That is possible, either Y_1 is equal to 0 or Y_2 equal to 3 or Y_1 is equal to 1, Y_2 is equal to 2 or Y_1 is equal to 2 or, and Y_2 is equal to 1 or Y_1 is equal to 3 and Y_2 is equal to 0.

Since Y_i 's are i.i.d. random variables, you can write down this as a probability of Y_1 is equal to 0 into probability of Y_2 is equal to 3 and so on. Probability of Y_1 is equal to 0, that is nothing but p_0 . Probability of Y_2 is equal to 3 that is nothing but p_3 . Similarly, the second expression is p_1 into p_2 ; third one is p_2 into p_1 ; the last one is p_3 p_0 . Since p_3 is equal to 0, the first term and the last term will be 0. So, you will get $p_1 p_2$ plus $p_2 p_1$ that is same as 6 by 25. So, this is the conditional probability of p of Z_2 is equal to 3 given Z_1 is equal to 2.

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Example 1. ...

► Similarly,

$$P(Z_3 = 2 \mid Z_2 = 3) = P(Y_1 + Y_2 + Y_3 = 2)$$

$$= p_0 p_0 p_2 + p_0 p_2 p_0 + p_2 p_0 p_0$$

$$+ p_1 p_1 p_0 + p_1 p_0 p_1 + p_0 p_1 p_1$$

► Now,


$$P(Z_2 = 2) = P(Z_2 = 2 \mid Z_1 = 0)P(Z_1 = 0)$$

$$+ P(Z_2 = 2 \mid Z_1 = 1)P(Z_1 = 1)$$

$$+ P(Z_2 = 2 \mid Z_1 = 2)P(Z_1 = 2)$$

$$= 0 + P(Y_1 = 2)P(Z_1 = 1)$$

$$+ P(Y_1 + Y_2 = 2)P(Z_1 = 2)$$

$$= p_2 p_1 + (p_0 p_2 + p_1 p_1 + p_2 p_0) p_2$$


Similarly, one can find P of Z 3 is equal to 2 given Z 2 is equal to 3, that is possible when Y 1 plus Y 2 plus Y 3 is equal to 2. So, the probability of Y 1 plus Y 2 plus Y 3 is equal to 2; we have six possibilities. Substitute the value of p naught, p 1, p 2, you will get the numerical value of this conditional probability. Similarly, one can find the probability of Z 2 is equal to 2 also. Probability of Z 2 is equal to 2, same as probability of Z 2 is equal to 2 given Z 1 is equal to 0 multiplied by probability of Z 1 is equal to 0 plus the combination with the probability of Z 1 is equal to 1, probability of Z 1 is equal to 2. Substitute the values, then you will get the probability of Z 2 is equal to 2.

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Probability Generating Function

► Let $\{Y_i, i = 1, 2, \dots\}$ be i.i.d. random variables each having the same distribution like Z_1 .

► Let $H(s)$ be probability generating function of Y_i .


$$H(s) = \sum_k P(Y_i = k) s^k = \sum_k p_k s^k, \quad |s| \leq 1$$

where s is a complex variable.

► Let $H_n(s)$ be probability generating function of Z_n .

$$H_n(s) = \sum_k P(Z_n = k) s^k, \quad |s| \leq 1$$

where s is a complex variable.



Now, we are going to discuss the probability generating function for the branching process. Let Y_i 's be i.i.d. random variables, each having the same distribution like Z_1 . Let $H(s)$ be the probability generating function of Y_i 's; let $H_n(s)$ be the probability generating function of Z_n .


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Probability Generating Function . . .

► Since $Z_0 = 1$, we have

$$H_0(s) = s$$

and

$$\begin{aligned} H_1(s) &= \sum_k P(Z_1 = k) s^k \\ &= \sum_k P(Z_1 = k \mid Z_0 = 1) s^k \\ &= \sum_k p_k s^k \\ &= H(s) \end{aligned}$$


Since Z_0 is equal to 1, you will get $H_0(s)$ is same as s . Now, our interest is to find out the probability generating function for Z_1 that is same as the probability generating function of Y_i 's. The probability generating function of Y_i 's is $H(s)$, therefore $H_1(s)$ is same as $H(s)$.

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Theorem 1: PGF of Z_n

► $H_n(s) = H_{n-1}(H(s))$ and $H_n(s) = H(H_{n-1}(s))$


► **Proof:** For $n = 1, 2, \dots$

$$P(Z_n = k) = \sum_i P(Z_n = k \mid Z_{n-1} = i)P(Z_{n-1} = i)$$

$$= \sum_i P(Y_1 + Y_2 + \dots + Y_i = k)P(Z_{n-1} = i)$$

► Now,

$$H_n(s) = \sum_k P(Z_n = k)s^k$$

$$= \sum_k \left[\sum_i P(Z_n = k \mid Z_{n-1} = i)P(Z_{n-1} = i) \right] s^k$$


Our interest is to find out the probability generating function for Z_i , Z_n , where n is 1, 2, 3 and so on. This we are going to give it as a theorem, H_n of s . This is nothing but the probability generating function for the random variable Z_n , is same as H of n minus 1 of H of s and H_n of s also can be written in the form of H of H_{n-1} of s . Let us see the proof of this.

We know that probability of Z_n is equal to k that is nothing but summation over i 's. Probability of Z_n is equal to k , given Z_{n-1} is equal to i multiplied by probability of Z_{n-1} is equal to i . We know, that this condition probability is nothing but probability of Y_1 plus Y_2 and so on plus Y_i is equal to k multiplied by probability of Z_{n-1} is equal to i .

Now, we will go for finding out the probability generating function for the random variable Z_n . Substitute probability of Z_n is equal to k from above in this equation. Therefore, you will have summation of k , substitute the probability of Z_n is equal to k , that is nothing but summation over i . Probability of a, conditional probability multiplied by probability of Z_{n-1} is equal to i multiplied by s power k .

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Theorem 1: PGF of $Z_n \dots$

▶

$$H_n(s) = \sum_i P(Z_{n-1} = i) \left[\sum_k P(Y_1 + Y_2 + \dots + Y_i = k) s^k \right]$$

▶ Since $\{Y_i, i = 1, 2, \dots\}$ are i.i.d. random variables and PGF of Y_i is $H(s)$, then the PGF of $Y_1 + Y_2 + \dots + Y_i$ is $[H(s)]^i$.

▶ Hence,

$$H_n(s) = \sum_k P(Z_{n-1} = i) [H(s)]^i = H_{n-1}(H(s))$$


Substitute, the conditional probability is nothing but the probability of Y_1 plus Y_2 plus so on. Y_i is equal to k into s power k . Since Y_i 's are i.i.d. random variables and the probability generating function of Y_i 's are nothing but H of s . The probability generating function of sum of i random variables Y_i 's, that is nothing but H of s whole power i because of Y_i 's are i.i.d random variables and probability generating function of Y_i 's is equal to H of s . Therefore, the probability generating function of Y_1 plus Y_2 and so on plus Y_i is H of s whole power i .

Therefore, substitute, this is nothing but the probability generating function of Y_1 plus Y_2 plus and so on plus Y_i . Therefore, H_n of s is nothing but summation over k H_n of s is nothing but summation over i probability of Z_{n-1} is equal to i times H of s whole power i , replace this by H of s whole power i , therefore summation i probability of Z_{n-1} is equal to i H of s whole power i . So, that is nothing, but the probability generating function for the random variable Z_{n-1} with the replacement s by H of s . Therefore, H_n of s is nothing, but H_{n-1} of H of s .

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Theorem 1: PGF of Z_n ...


- ▶ We know that $H_1(s) = H(s) = H(H_0(s))$ since $H_0(s) = s$.
- ▶ Suppose for $n = j$,

$$H_j(s) = H(H_{j-1}(s))$$

then

$$\begin{aligned} H_{j+1}(s) &= H_j(H(s)) \\ &= H(H_{j-1}(H(s))) \\ &= H(H_j(s)) \end{aligned}$$

- ▶ By induction, it is proved.



So, the first part is proved. H_n of s is same as H_{n-1} of H of s . Now, we are going to prove the second part. We know, that H_1 of s is H of s , that is same as H of H naught of s because H naught of s is nothing, but s . Suppose this is true for n is equal to j , that means, H, H of j of s is H of H of $j-1$ time of s . Then, we can find out what is H of $j+1$ of s ? That is nothing, but H_j of H of s that is same as H of H_{j-1} times H of s that is same as H of H_j of s . By induction it is proved.


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Theorem 2: Moments of Z_n

- ▶ Let $\mu = E(Z_1)$ and $\sigma^2 = Var(Z_1)$.
- ▶ Then

$$E(Z_n) = \mu^n$$

and

$$Var(Z_n) = \begin{cases} \frac{\mu^{n-1}(\mu^n - 1)\sigma^2}{\mu - 1}, & \mu \neq 1 \\ n\sigma^2, & \mu = 1 \end{cases}$$


Now, we are finding the moments of Z_n . Let μ is equal to expectation of Z_1 and sigma square is nothing but the variance of Z_1 . Then, expectation Z of n , that is μ^n and the variance of Z_n will be for μ equal to 1. It is n times sigma square for μ is not equal to 1. It will be $\mu^n - 1$ times sigma square divided by $\mu - 1$.


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Theorem 2: Moments of $Z_n \dots$

- ▶ **Proof of Part 1:** By Theorem 1, we have $H_n(s) = H_{n-1}(H(s))$.
- ▶ Then differentiating and putting $s = 1$, $H'_n(1) = H'_{n-1}(H(1))H'(1)$
- ▶ We know that, $H(1) = 1$, $H'(1) = \mu$ and for $n = 1, 2, \dots$

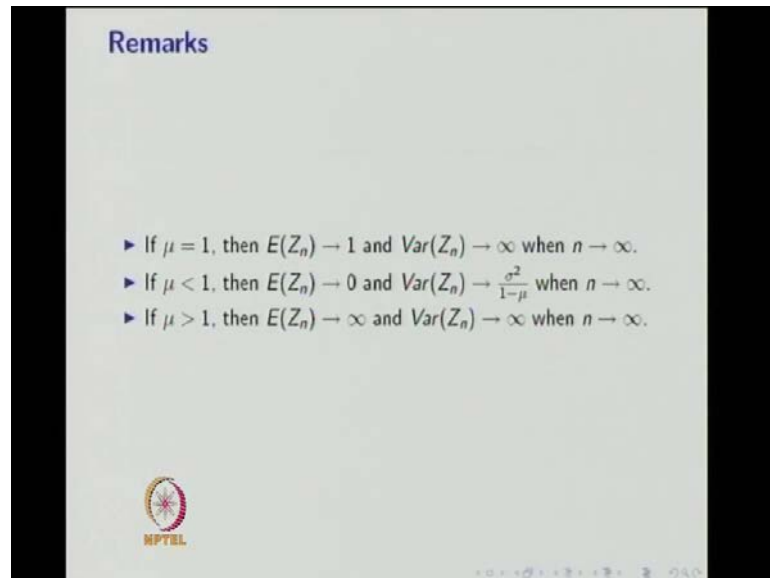
$$H'_n(1) = H'_{n-1}(1)\mu = \dots = \mu^n$$

- ▶ Hence $E(Z_n) = \mu^n$.




We prove the part 1, that is, expectation of Z_n is equal to μ^n . By theorem 1, you, we know that $H_n(s)$ is $H_{n-1}(H(s))$. Then, differentiating and putting s equal to 1 we will, we will get $H'_n(1)$ that is same as $H'_{n-1}(H(1))H'(1)$ into $H'(1)$. We know, that $H(1) = 1$, $H'(1) = \mu$. Therefore, for n , n is equal to 1, 2 and so on. We will get $H'_n(1)$ is same as $H'_{n-1}(1)\mu$ that is same as $H'_{n-2}(1)\mu^2$ and so on. Therefore, you will get μ^n because you know that $H'(1)$ is μ . By recursively you will get, $H'_n(1)$ is μ^n . Therefore, expectation of Z_n is nothing, but $H'_n(1)$ that is same as $(())$.

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Remarks


- ▶ If $\mu = 1$, then $E(Z_n) \rightarrow 1$ and $\text{Var}(Z_n) \rightarrow \infty$ when $n \rightarrow \infty$.
- ▶ If $\mu < 1$, then $E(Z_n) \rightarrow 0$ and $\text{Var}(Z_n) \rightarrow \frac{\sigma^2}{1-\mu}$ when $n \rightarrow \infty$.
- ▶ If $\mu > 1$, then $E(Z_n) \rightarrow \infty$ and $\text{Var}(Z_n) \rightarrow \infty$ when $n \rightarrow \infty$.

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So, till now we have discussed the probability generating function of Z power n and also, we have discussed mean and variance of Z of n . As a remark, if μ is equal to 1, the expectation, expectation of Z_n tends to 1, whereas variance of Z_n tends to infinity as n tends to infinity. You can see it from this theorem, as μ tends to 1, expectation of Z_n will tends to 1, whereas the variance Z_n tends to infinity because that is same as n times sigma square. Therefore, as μ tends to 1, the variance of Z_n tends to infinity as n tends to infinity.

Whereas if μ is less than 1, the expectation of Z_n tends to 0 and variance of Z_n will be sigma square divided by $1 - \mu$ as n tends to infinity. Similarly, if μ is greater than 1, then the expectation of Z_n will tends to infinity and the variance of Z_n tends to infinity as n tends to infinity. This also you see it from the theorem.

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Criticality

- ▶ A very important classification is based on the mean progeny count $\mu = E(Z_1)$.
- ▶

$$E(Z_n) = \mu^n$$

Therefore, in the expected value sense, the process grows geometrically if $\mu > 1$, stays constant if $\mu = 1$, and decays geometrically if $\mu < 1$.

- ▶ These three cases are called supercritical, critical, and subcritical, respectively:

$$\begin{aligned} \mu > 1, & \text{ supercritical } E[Z_n] \uparrow \infty \\ \mu = 1, & \text{ critical } E[Z_n] = 1 \\ \mu < 1, & \text{ subcritical } E[Z_n] \downarrow 0 \end{aligned}$$

Now, we are going to discuss the criticality. A very important classification is based on mean, progeny, progeny count μ is equal to expectation of Z_1 ; a very important classification is based on the mean progeny count μ is equal to expectation of Z_1 .


You know, that expectation of Z_n is equal to μ^n , just now we have proved it in the theorem 1. Therefore, in the expected value sense the process grows geometrically if μ is greater than 1, stays constant if μ is equal to 1 and decays geometrically if μ is less than 1. From the expectation of Z_n is equal to μ^n , you can conclude if μ is greater than 1. The process grows geometrically if μ is equal to 1, then the process stays constant, whereas if μ is less than 1, the process decays geometrically. Thus three cases are called supercritical, critical and subcritical respectively.

That means, if μ is greater than 1, then the process is called supercritical, in this case the expectation of Z_n tends to infinity. The μ is equal to 1, the process is called critical and the expectation of Z_n is equal to 1 as n tends to infinity. When μ is less than 1, the process is called subcritical and expectation of Z_n will tends to 0 as n tends to infinity.

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Example 2.

- ▶ Consider the Galton - Watson process $\{Z_n, n = 0, 1, 2, \dots\}$ with offspring distribution $\{p_k\}$.
- ▶ Assume that $p_0 = 1/5, p_1 = 3/5$ and $p_2 = 1/5$.
- ▶ Then $\mu = E(Z_1) = 1$.
- ▶ Hence, this process is a critical Galton - Watson process.
- ▶ $E(Z_1^2) = \frac{7}{5}$, then $\sigma^2 = \frac{2}{5}$.
- ▶ Hence, for $n = 1, 2, \dots$

$$E(Z_n) = 1 \text{ and } \text{Var}(Z_n) = \frac{2n}{5}$$


Now, we are going to consider the second example. Consider the Galton-Watson process Z_n with offspring distribution p_k , which is the same problem, example 1, with the assumption p_0 is equal to $1/5$, p_1 is equal to $3/5$ and p_2 is equal to $1/5$.

Now, you can find out the mean of Z_1 , that is nothing but 1 because p_0 is equal to $1/5$, p_1 is equal to $3/5$, p_2 is equal to $1/5$, you will get mean of Z_1 will be 1. Hence this process is called critical Galton-Watson process because μ is equal to 1. We can find out the variance of Z_1 also, first we find out expectation of Z_1 square that will be $7/5$. Hence variance equal to expectation of Z_1 square minus expectation of Z_1 whole square, that will be $2/5$.


Since you know μ and σ^2 using the theorem 1, you can find out the moments of Z_n , first and second order moment expectation of Z_n and variance of Z_n . Since μ is equal to 1 the expectation of Z_n will be 1, variance of Z_n will be n times σ^2 . In this problem the σ^2 is $2/5$, therefore mean of Z_n is 1, variance of Z_n is $2n/5$.

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Probability of Extinction

- ▶ If $Z_n = 0$ for some value $n \geq 1$, then $Z_m = 0$ for all $m \geq n$ and also

$$P(Z_m = 0 \mid Z_n = 0) = 1, \text{ for all } m \geq n$$
- ▶ We say that a branching process is extinguished when $P(Z_n = 0) = 1$, for some value of $n = 1, 2, \dots$




Now, we are going to discuss the very important concept called probability of extinction. If Z_n equal to 0 for some value for n is greater than or equal to 1, then Z_m will be 0 for all m greater than or equal to n and also the conditional probability of Z_m is equal to 0, given Z_n is equal to 0, that will be 1 for all m greater than or equal to 1. We say, that the branching process is, extent, extinguished when probability of Z_n is equal to 0 will be 1 for some value of n .

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Theorem 3: Probability of Extinction

1. If $\mu \leq 1$, then the probability of extinction is one.
2. If $\mu > 1$, then the probability of extinction is the positive root less than unity of the equation $H(s) = s$.

- ▶ **Proof:** Let d_n be the probability that extinction occurs at or before the n -th generation, i.e., $d_n = P(Z_n = 0)$.
- ▶ We know that, $d_0 = 0$.
- ▶ Now,

$$\begin{aligned}
 d_{n+1} &= P(Z_{n+1} = 0) \\
 &= P(Z_{n+1} = 0 \mid Z_n = 0)P(Z_n = 0) \\
 &\quad + P(Z_{n+1} = 0 \mid Z_n \neq 0)P(Z_n \neq 0) \\
 &= 1 \times P(Z_n = 0) \\
 &\quad + P(Z_{n+1} = 0 \mid Z_n \neq 0)P(Z_n \neq 0) \\
 &\geq P(Z_n \neq 0) = d_n
 \end{aligned}$$


Now, we discuss the probability of extinction in theorem 3. If μ is less than or equal to 1, then the probability of extinction is 1. If μ greater than 1, then the probability of extinction is the positive root less than unity of the equation H of s is equal to s , where H of s is the probability generating function of Z_1 .

Here we consider a Galton-Watson branching process Z_n with offspring distribution p_k and p_k forms the probability mass function for the random variable Z_1 . If μ is less than or equal to 1, then the probability of extinction is 1. If μ is greater than 1, then the probability of extinction is the positive root less than unity of the equation H of s equal to s , that means, we have to solve the equation H of s is equal to s . From that you can get the probability of extinction where μ is the mean of the random variable Z_1 .

Let us see the proof. Let d_n be the probability, that extinction occurs at or before the n th generation. Hence, d_n is nothing but the probability of Z_n is equal to 0. We know, that d_0 will be 1 because we made the assumption Z_0 is equal to 1. Now, we will find out d_{n+1} . d_{n+1} is nothing but, by the definition, it is d_{n+1} , is nothing but probability of Z_{n+1} equal to 0.

We can write probability of Z_{n+1} equal to 0 using conditional probabilities, that is same as probability of Z_{n+1} is equal to 0, given Z_n was 0 multiplied by probability of Z_n is equal to 0 plus probability of Z_{n+1} is equal to 0 given Z_n is not equal to 0 multiplied by probability of Z_n is not equal to 0. We know, that probability of Z_{n+1} is equal to 0 given Z_n is equal to 0, that is equal to 1. Therefore, this will be 1 times probability of Z_n is equal to 0 plus probability of Z_{n+1} is equal to 0 given Z_n is not equal to 0 multiplied by probability of Z_n not equal to 0. Obviously, this will be greater than equal or equal to probability of Z_n is not equal to 0 because we are adding some probability plus probability multiplied by probability of Z_n is not equal to 0. Therefore, this quantity will be greater than or equal to probability of Z_n not equal to 0.

This quantity, this quantity will be, this is same as 1 times probability of Z_n is equal to 0 plus probability of Z_{n+1} equal to 0 given probability of Z_n is not equal to 0 multiplied by probability of Z_n is not equal to 0. Obviously, this quantity will be greater than or equal to 0, the second term. Therefore, the whole result will be greater than or equal to probability of Z_n equal to 0. You know, that probability of Z_n is equal to 0 is


nothing but d_n , therefore d_{n+1} will be greater than or equal to d_n . This is true for n is equal to 1, 2 and so on.

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Theorem 3: Probability of Extinction ...

- Hence,

$$0 = d_0 \leq d_1 \leq \dots \leq 1$$
- $\{d_n, n = 0, 1, \dots\}$ is an increasing and upper bound sequence, there exists $d = \lim_{n \rightarrow \infty} d_n$, $d \in [0, 1]$ and d is the probability of extinction of the process.

$$\begin{aligned}
 d_m &= P(Z_m = 0) \\
 &= \sum_j P(Z_m = 0 \mid Z_1 = j) P(Z_1 = j) \\
 &= \sum_j P(Z_m = 0 \mid Z_1 = j) p_j
 \end{aligned}$$


Hence, d_0 will be 0. d_0 is less than or equal to d_1 , d_1 will be less than or equal to d_2 and so on. And since d_i 's are the probability of extinction, therefore that will be less than or equal to 1. Hence, d_n is a sequence and upper bound sequence. d_n is an increasing and upper bound sequence, there exists d , that is nothing but the limit n tends to infinity of d_n and the d is belonging to the closed interval 0 to 1 and d is the probability of extinction of the process.

Now, we will find out what is the d ? You know, that d_m is nothing but probability of Z_m equal to 0, that is nothing but summation over j probability of Z_m is equal to 0 given Z_1 is equal to j multiplied by probability of Z_1 is equal to j . You know, that probability of Z_1 is equal to j is nothing but p_j . Therefore, the d_m is nothing but summation over j probability of Z_m is equal to 0 given Z_1 is equal to j multiplied by p_j .

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Theorem 3: Probability of Extinction . . .

► We have


$$\begin{aligned} P(Z_m = 0 \mid Z_1 = j) &= P(Y_1 + Y_2 + \dots + Y_j = 0) \\ &= P(Y_1 = 0)P(Y_2 = 0) \dots P(Y_j = 0) \\ &= [P(Z_{m-1} = 0)]^j \\ &= d_{m-1}^j \end{aligned}$$

► Hence,

$$d_m = \sum_j d_{m-1}^j p_j = H(d_{m-1})$$

► Since $d_m \rightarrow d$ when $m \rightarrow \infty$, the value d satisfies the equation $s = H(s)$.

► Note that the solutions to equation $s = H(s)$ represent intersections of the graphs of $y = s$ and $y = H(s)$.



We know, that probability of Z_m is equal to 0 given Z_1 is equal to j is nothing but probability of Y_1 plus Y_2 plus and so on. Y_j is equal to 0 since Y_i 's are i.i.d. random variables, that is nothing but probability of Y_1 is equal to 0 Y_2 is equal to 0 and so on. Probability of Y_j is equal to 0 that is same as the probability of Z_{m-1} equal to 0 whole power j , that is nothing but d_{m-1} power j .

Hence, you can substitute this result in this equation. This conditional probability is nothing but d_{m-1} power j . Therefore, d_m will be summation over j , d_{m-1} power j p_j and that is nothing but the probability generating function of d_{m-1} . So, hence we get d_m is equal to H of d_{m-1} . Since d_m tends to d as m tends to infinity, the value d satisfies the equation s is equal to H of s because d_m is equal to H of d_{m-1} . Therefore, the value d satisfies the equation s is equal to H of s .

Note, that the solution to the equation s is equal to H of s represents intersections of the graphs of Y is equal to s and Y is equal to H of s . So, the d will be probability of extinction and we are not going to discuss furthermore about how to solve s is equal to H of s and finding the probability of extinction.

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Example 2.

- ▶ Consider the Galton-Watson process $\{Z_n, n = 0, 1, 2, \dots\}$ with offspring distribution $\{p_k\}$.
- ▶ Assume that $p_0 = 1/5$, $p_1 = 3/5$ and $p_2 = 1/5$.
- ▶ Then $\mu = E(Z_1) = 1$.
- ▶

$$H(s) = \sum_k p_k s^k = \frac{1}{5} + \frac{3}{5}s + \frac{1}{5}s^2$$

- ▶ For instance, we find

$$P(Z_2 = 2) = \frac{H_2''(0)}{2!}$$

using

$$H_2(s) = H(H(s)) = \frac{1}{5} + \frac{3}{5}H(s) + \frac{1}{5}[H(s)]^2$$

- ▶ Since $\mu = 1$, by Theorem 3, the probability of extinction is one.

We will consider the third example, Z_n be the sequence of random variable, which is a Galton-Watson process with offspring distribution p_k . Similar to the example 1 and 2, p_0 is equal to 1 by 5, p_1 is equal to 3 by 5, p_2 is equal to 1 by 5. Already we got the mean of Z_1 that is equal to 1; therefore, this is the critical Galton-Watson process.

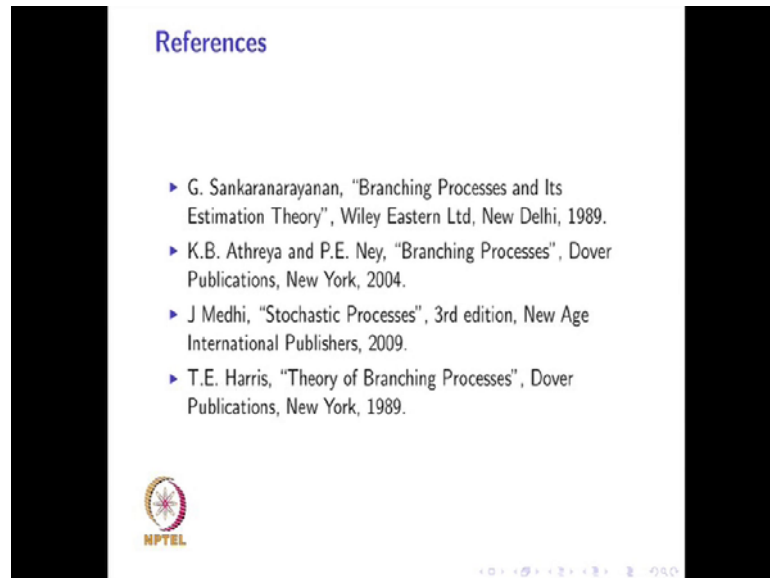
Now, you can find out the probability generating function of Z_1 . Using this one can find the probability of Z is equal to or we can find the distribution of Z_n also. For instance, we find probability of Z is equal to 2, for that we, you need the probability generating function of Z_2 , that means, you should know what is the probability generating function of H_2 of s .

With the help of H_1 of s and H of s , one can find the H_2 of s that is what we have proved it in the theorem 2. H_n , H_n of s will be H_{n-1} of H of s . So, here we put n is equal to 2, find the probability generating function of Z_2 using the probability generating function of Z_1 . We are finding the probability of Z_2 is equal to 2. So, probability of Z is equal to 2 will be $H_2''(0)$ divided by 2 factorial.

So, first you find out H_2 of s that is nothing but H_1 of H of s that is same as H of H of s . So, replace s by H of s in the H of s expression, that is, $1/5$ plus $3/5$ times s plus $1/5$ by s square. So, replace s by H of s , you will get H_2 of s . Once you know H_2 of s , you differentiate twice, then substitute s is equal to 0, then divide by 2, you will get the probability of Z_2 is equal to 2. Since μ is equal to 1, this is the critical Watson process.

By using theorem 3 we conclude the probability of extinction is 1. Theorem 3 says, if μ is less than or equal to 1, then the probability of extinction is 1. So, since in this problem the μ is equal to 1, hence by theorem 3 the probability of extinction is 1.

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So, in this lecture we have covered the definition and the examples of a branching process, in particular we have discussed Galton-Watson discrete branching process. We have discussed probability generating function of Z_n ; we have discussed mean and variance of Z_n . Also, we have seen three examples, through that we found the conditional probability, probability generating function mean and variance of Z_n . Finally, we have discussed probability of extinction for the Galton-Watson process.

In the next lecture we are going to cover another important branching process, that is, Markov branching process, which is a continuous type branching process. In this lecture we have discussed discrete type branching process, that is, Galton-Watson process. In the next lecture we are going to cover continuous type branching process, that is, Markov branching process and some more important branching processes. Here are the references.