Probability mass function formula

The probability mass function (PMF) is also known as a probability function or frequency function that characterizes the distribution of discontinuous random variables. Note that X is a discontinuous random variable of the function, the random probability mass function of the random variable X is given by Px(x)=X(X=x), and all x belong to the X range: Px (x) ≥0 and ∑xεRange(x) px (x) = 1 range (X) are countable set values and can be written as x.1.1. This means that the random variable X is the value x1, x2, x3、.. It means to take. The defined probability mass function is defined for all values in R and takes all arguments for any real number. If the value of the argument is equal to zero, and the argument belongs to x, the PMF value must be positive. Probability mass functions are usually the main elements that define discrete probability distributions, but they differ from probability density functions (PDFs) with different results. This is why probability mass functions are used for computer programming and statistical modeling. That is, the probability mass function is a function that associates discrete events with probabilities related to the event that occurred. The word mass indicates the probability of concentrating on discrete events. What is the difference between PMF and PDF? Difference between PMF and PDF: PMF PDF solution uses discontinuous random variables where the range solution between the number of discrete random variables is within the range of continuous random variables Use continuous random variables Use continuous random variables, read: Applied probability mass function of probability mass function plays an important role in statistics. This defines the probability of a random variable of the specified discontinuity. It integrates a specified random number of variables equal to the probability of a random variable. Used to calculate the mean and variance of discrete distributions. Find probability values that are used in binomial and Poisson distributions and use discrete values. Some of the examples of probability mass functions using binomial and Poasson distributions are: For the PMF binomial distribution of binomial distributions, consider an example in which pmf includes 10 multiple choices in a trial that calculates the number of votes of two different candidates in a company that finds the number of defective products in a production run to find the number of successful sales calls. To search for probabilities正しい答えと正しくない回答を使用すると、確率質量関数が使用されます。 ポワソン分布のPMF同様に二項、PMFはポワソン分布の用途も有する。 特定の製品に対する毎月の需要を求める銀行に到着する顧客の時間数を計算する 特定のウェブサーバーへのアクセス数を1時間ごとに見つける PMFテーブルの例での誤字数の検索 確率質量関数の例は以下の通り:質問:Xをランダム変数にし、P(X=x)はPMFです。 X 0 1 2 2 3 4 5 6 7 P(X=x) 0 k 2k 2k 2k 3k k2 2k2 7k2+k の値を決定する 確率を見つける (i) P(X≤ 6), (ii) P(3<x≤ 6=)= solution= := (1)= we= know= that;= ∑p(xi)=1 therefore,= 0= += k= += 2k= += 2k= += 3k= += k2= += 2k2= += 7k2+= k=1 9k= += 10k2=1 10k2= += 9k= –= 1=0 10k2= += 10k= –= k= -1=0 10k(k= += 1)= -1(k= += 1)=0 (10k= –= 1)= (= k= += 1=)=0 so,= 10k= –= 1=0 and= k= += 1=0 therefore,= k=1/10 and= k=-1 k=-1 is= not= possible= because= probability= value= ranges= from= 0= to= 1.= hence,= the= value= of= k= is= 1/10.= (2)= (i)= p(x= ≤= 6)=1 –= p(= x=> 6) = 1 - (7k2+k) = 1 - (7(1/10)2 + (1/ 10)) = 1 – (7/100 + 1/10) = 1 - (17/100) = = (100 – 17)/100 = 83/100、P(X≤6) = 83/100 (ii) <x≤ 6=)=P(x=4) += p= (= x=5)= += p= (= x=6) == 3k= += k2= += 2k2=(3/10) += (1/10)2= += 2= (1/10)2=3/10 += 1/100= += 2/100=3/10 += 3/100=(30+3)/100=33/100></x≤> <x≤ 6=)=33/100. for= more= information= about= probability= mass= function= and= other= related= topics= in= mathematics,= register= with= byju's= –= the= learning= app= and= watch= interactive= videos.= discrete-variable= probability= distribution= the= graph= of= a= probability= mass= function.= all= the= values= of= this= function= must= be= non-negative= and= sum= up= to= 1.= in= probability= and= statistics,= a= probability= mass= function= (pmf)= is= a= function= that= gives= the= probability= that= a= discrete= random= variable= is= exactly= equal= to= some= value. [1]= sometimes= it= is= also= known= as= the= discrete= density= function.= the= probability= mass= function= is= often= the= primary= means= of= defining= a= discrete= probability= distribution,= and= such= functions= exist= for= either= scalar= or= multivariate= random= variables= whose= domain= is= discrete.= a= probability= mass= function= differs= from= a= probability= density= function= (pdf)= in= that= the= latter= is= associated= with= continuous= rather= than= discrete= random= variables.= a= pdf= must= be= integrated= over= an= interval= to= yield= a= probability. [2]= the= value= of= the= random= variable= having= the= largest= probability= mass= is= called= the= mode.= formal= definition= probability= mass= function= is= the= probability= distribution= of= a= discrete= random= variable,= and= provides= the= possible= values= and= their= associated= probabilities.= it= is= the= function= p= := r= {\displaystyle= p:\mathbb= {\mathbb= {r}= }= }= →= [= 0= ,= 1=]= {\displaystyle= \rightarrow= [0,1]}= defined= by= p= x= (= x= i=)=P (= x=x i=)= {\displaystyle= p_{x}(x_{i})=P(X=x_{i})} for= −= ∞=></x≤> < x=> < ∞ ∞=></ ∞ > P(3)</x≤>-\infty <> <\infty }= ,[2]= where= p= {\display= p}= is= a= probability= measure.= p= x= (= x=) = {\displaystyle= p_{x}(x)}= can= also= be= simply= as= p= (= x=) = {\displaystyle= p(x)}= . [3]= the= properties= associated= with= each= possible= values= must= be= positive= and= sum= up= to= 1.= for= all= others= values, = the= properties= need= to= be= 0.= ∑ p= x= (= x= i=) = 1\displaystyle= \sum= p_{x}(x_{i})=1} p= (= x= i=)=>0 {\displaystyle p(x_{i})>0} p (x) = 0 {\displaystyle p(x)=0} Considering all other x probabilities as mass is the result of all assumptions x {\displaystyle x} physical mass is stored as a total probability of , which helps avoid mistakes. Theoretical formula measurement The probability mass function of the discontinuous random variable X {\display style X} can be seen as a special case of two common measures: the distribution of X {\display style X} and the probability density function of X {display style X} for count measures. Here's more accurately: (A, A, P) {{{{\mathcal {A},P) is a probability space, and (B, B) {{\display style (B,{{\math {B}}) is a measurable space where the underlying σ alms are discrete, especially if it contains a single set of B {\displaystyle B}. In this setting, the random variable X: a → B {\displaystyle X\colon A\to B} is discontinuous if the image can be counted. Push-forward measure X ∗ (P) {{display style X_ {}(P)} is called the distribution of X {\displaystyle X} in this context, and restrictions on singleton sets induce probability mass function f X B {\displaystyle B} probability scale→ R {\display style f_ {X} colon B\to \math {R} f X (b) = P (X - 1 (b) = = [X ∗ (P) ({ b) { { {Display Style f_ {X}(b)=P(X^{-1}(b)=[X_{*}](P)(b)(B)∈ B {\Display style b\in B}Then (B, B, μ){{{{\mathcal {B},\mu}} is a measurement space with μ counting. The probability density function f {\display style f} of X {\display style X} for the count measure, if any, is the Radon-Nicodim derivative (for counting criteria) of the push-forward measure of X {\displaystyle X}, so f = d X ∗ P / d μ {\displaystyle f=dX_{*}P/d\mu} and f {\displaystyle f} are functions from B {\displaystyle B} to non-negative real numbers. As a result, for B ∈ B {\display style b\in B}, P (X = b) = P (X - 1 ({ b }) : = ∫ X - 1 ({ b }) d P = {X=b) = P (X^{-1}) = = = = = = = ==B \int _{X^{1}(\{b\}}}}}dP=} ∫ { b } f d μ = f (b) , {\display style \int _{b\}fd\mu =f(b), f {\displaystyle f} is actually a probability mass function. Potential results If there is a natural order in x {\displaystyle x}, it may be useful to assign a number (in some cases n Tuple </\infty>discrete multi-variable random variables) and values that are not in the X {\display style X} image should also be considered. This means that f X {\displaystyle f_ {X}} is defined for all real numbers, and f X (x) = 0 {\display style f_ {X}(x)=0} can be defined for all x ∉ x x (S) {\display style xotin X(S)}. The image in X {\Display Style X} has a countable subset with the probability mass function f X (x) {\Display Style f_ {X}(x)}. Therefore, the probability mass function is zero for all values except the number of values in x {\display style x}. The discontinuity of the probability mass function is related to the fact that the cumulative distribution function of discrete random variables is also discontinuous. If X {\display style X} is a discontinuous random variable, P (X = x) = 1 {\display style P(X=x)=1} means that the casual event (X = x) {\display style (X=x)} is certain (100% of occurrences). Conversely, P (X = x) = 0 {\Display style P(X=x)=0} means that casual events (X = x) {\display styles (X=x)} are always not possible. This statement does not apply to the contiguous random variable X {\displaystyle X}, but in that case, P (X = x) = 0 {\Display style P(X=x)=0} is for any x {{\displaystyle x}, by definition, a continuous random variable can have an infinite set of values, so the probability of having a single specific value x is 1 ∞ = 0 {\ frac {1} equal to {\infty}=0}. Discreteness is the process of converting a continuous random variable into a discontinuous variable. Examples of the main articles: Bernouy distribution, binomial distribution, and geometric distribution finite, Bernoui distribution, binomial distribution, geometric distribution. The Bernouy distribution Ber(p) is used to model experiments that contain only two possible results. The two results are often encoded as 1 and 0. p X (x) = { p , x is 1 1 - p, if x is 0 {\display style p_ {X}(x)={{case}p,&{text{}x\text{1}}}}\1-p{\text{{{{{\text{{{{{{{{\text{0}\end{cases}}S {\display style S} Let's say that X {\display style X} is a random variable defined in S {\display style S}, which assigns 0 to category tails and 1 to category head. Because coins are fair, the probability mass function is p X (x) = { 1 2 , x ∈ { 0 , 1 } , 0 , x ∉ { 0 , 1 } . {\Display style p_{X}(x)={{{{case}{{frac {1}{2}},&x\in\{{0,1\},\0,&xotin \{{0,1\\\End{Case}}Bin(n,p) models the number of successes if someone draws n times in substitution. Each draw or experiment is independent and produces two results. The associated probability mass function is (n k) p k (1 - p) n - k{\binom {n}{k}}p^{k}(1-p)^{n-k}}Fairdai probability mass function. All numbers on the die are equal in chance of appearing on top when the die no longer rolls. An example of binomial distribution is the probability of getting exactly 1 6 when someone does three fair die rotations. The geometric distribution represents the number of attempts required to obtain a single success, which is written as Geo(p). Its probability mass function is p X (k) = (1 - p) k - 1 p {\display style p_ {X}(k)=(1-p)^{k-1}p}. An example is tossing a coin until the first head appears. Other distributions that can be modeled using the probability mass function are categorical distributions (also known as generalized Bernouy distributions) and polynomial distributions. If there are two or more categories in the discrete distribution, one of them can occur, and if there is a single trial (drawing), whether or not these categories have a natural order, this is a category distribution. Examples of multi-variable discrete distributions and their probability mass functions are provided by polynomial distributions. Where multiple random variables are the successes of each category after a certain number of attempts, and each non-zero probability mass indicates the probability of a specific combination of successes in different categories. The infinite exponential distribution exponential distribution is an example of a distribution with an infinite number of results. {\display style {\text{Pr}}(X=i)={\frac {1}{2^{i}\quad {{{for}}}\quad i=1,2,3,\dot.} Despite the infinite number of results, the total probability mass is 1/2 + 1/4 + 1/8 + 1.1, which meets the total requirement for probability distribution probabilities. Multi-random case Main article: Joint probability distribution Two or more discontinuous random variables have a joint probability mass function that gives the probability of each possible combination of random variable realizations. See ^ Stewart, William J. (2011). Probabilities, Markov Chains, Queues, and Simulations: Mathematical Foundations of Performance Modeling. Princeton University Press p. 105.ISBN 978-1-4008-3281-1.^ a b Modern introduction to probabilities and statistics : Understand why and how. Decking, Michelle, 1946-.London: Springer. 2005. ISBN 978-1-85233-896-1.OCLC 262680588.CS1 Maint: Others (link) ^ Rao, Singyres S., 1944- (1996). Engineering Optimization : Theory and Practice (Part 3: New York: Wiley. ISBN 0-471-55034-5.OCLC 62080932.CS1 maint: Multiple names: author list (link) Read more about Johnson, N. L.; Cots, S. Kemp, A. (1993). 1 Random discrete distribution (2nd) Wiley. p. 36.ISBN 0-471-54897-9.Source