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## ON ORDER <br> STATISTICS

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## اهدي هذا الجهـ المتواضع الى

الى من جعل الله الجنة تحت اقدامها والتي تعجز الكلمات عن وصفها
(امي الغالية)
الى رفيق دربي وحبيب قلبي سندي وشريك روحي
(زوجي العزيز)
الى كل من ساندني في مسيرتي الار اسية لهم كل المودة

## الثشكر و التقّبير

اتقام بالثشكر أولاً للباري(عزّ وجل) الذي وفقني في انجاز هذا
 من وقفة نعود الى اعوام قضيناهاها في رحاب الجامعة مع اسـا الاكارم الذين قـموا النا الكثير باذلين بذلك جهوداً كبيرة في بناء جيل الغد لتبعث الأمة من جديد ...

اتقام بجزيل الثكر والامتتـن الى استالذتي العزيزة الفاضلة أ.م.د. جنان حمزه فرهود المشرفة على البحث
وقبل ان امضي اقدم اسمى آيات الثككر والامتتان والثقيّير والمحبة الى الأين حملوا أقدس رسالة في الحياة ... الى الأين مهـواوا لنا طريق الطلم والمعرفة أساتنتي الافاضل.

رقية ياس

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## Contents

| Subjecct | page |
| :---: | :---: |
| Introduction | 1 |
| OrderStatistics | 2 |
| The Distribution of the Minimum | 4 |
| The Distribution of the Maximum | 7 |
| The Joint Distribution of the Minimum and Maximum | 9 |
| The Joint Distribution for All of the Order Statistics | 13 |
| The Distribution of $X_{(i)}$ | 16 |
| The Joint Distribution of $X_{(i)}$ and $X_{(j)}$ for $i<j$ | 19 |
| References | 21 |

## Introduction

We introduce in this research subject on order statistics such that suppose we have $n$ independent, identically random varibles, and we are asked to calculate the expected value of the minimum or maximum of them. We can do this using order statistics. If we sort these random varibles from least to greatest, the $K^{t h}$ order statistic is the $K^{t h}$ variable in our list. We often use the notation $X_{i}$ to refer to the $i^{t h}$ order statistic .for example, $X_{(1)}$ (the first order statistic) is the minimum of the random variables, $X_{(2)}$ (the second order statistic) is the second smallest, and so on, $X_{(n)}$ (the $\mathrm{n}^{\text {th }}$ order statistic) is the maximum.

Since we are discussing a set of random variables which all share the same distribution, it is useful to refer to the probability density function (p.d.f.) of that distribution as $f(x)$ and the cumulative distribution function (c.d.f.) as $F(x)$. In order to answer most questions about $X_{i}$, we need to find the pdf for $X_{i}$. We do this by first finding the (c.d.f.) for $X_{i}$ and then taking a derivative.

Also ,we explain some concepts about the order statistics such that the distribution of the minimum and distribution of the maximum and the joint distribution of the minmum and maximum.

In this research we offer some remarks, theorems and examples about the order statistics.

## Order Statistics

Suppose that $X_{(1)}, X_{(2)}, \ldots . X_{(n)}$ are $n$ jointly distributed random variables from a continuous function with continuous c.d.f. $F_{x}(x)$ and p.d.f. $f_{x}(x)$. The corresponding order statistics are the $X_{i}$ arranged in nondecreasing order. The smallest of the $X_{i}$ is denoted by $X_{1}$ the second smallest is denoted by $X_{2} \ldots \ldots$, and, finally the largest is denoted by $X_{n}$.

The order statistics of n-identically independently. distributed (iid) random variables $X_{(1)}, X_{(2)}, \ldots . X_{(n)}$ p.d.f. $f(x)$ are the values placed in ascending order,
that is, $a<Y_{1}<Y_{2}<\ldots<Y_{n}<b$ where $Y_{1}=\min \left\{X_{i}\right\}, Y_{2}$ the next $\min \left\{X_{i}\right\}$, and $Y_{n}=\max \left\{X_{i}\right\}$.

## Remark (1)

Although $X_{i}$ are iid random variables, the random variables $Y_{i}$ are neither independent nor identically distributed Thus, the minimum of $X_{i}$ is $Y_{1}=\min \left(X_{1}, X_{2}, \ldots X_{n}\right)$ and the maximum of $X_{i} Y_{n}=\max \left(X_{1}, X_{2}, \ldots X_{n}\right)$
The order statistics of the sample $X_{1}, X_{2}, \ldots X_{n}$ can also be denoted by $X_{(1)}, X_{(2)}, \ldots . X_{(n)}$ where $X_{(1)}<X_{(2)}<\ldots .<X_{(n)}$.

Here $X_{(k)}$ is the $k^{t h}$ order statistic and is equal to $Y_{k}$ in definition one of the most commonly used order statistics is the median the value in the middle position in the sorted order of the Values

## i.e, we denote the order statistics by:

$$
X_{(1)}=\min \left(X_{1}, X_{2}, \ldots X_{n}\right)
$$

$$
\begin{aligned}
& X_{(2)}=\text { the 2nd Smallest of }\left(X_{1}, X_{2}, \ldots X_{n}\right) \\
& \vdots=\vdots \\
& X_{(n)}=\max \left(X_{1}, X_{2}, \ldots . X_{n}\right)
\end{aligned}
$$

## Remark (2)

1- In the definition of order statistics it is not required that the $\left\{Y_{i}\right\}$ be independent identically distributed (iid).

2- the formal difintion above only works for continuous variables
3- We will assume that the n independent observations come from a continuous distribution, thereby making the probability zero that any tow observations are equal.

By difintion, every observation in a random variable has the same pdf. For example. if a set of four measurements is taken from a normal distribution with $\mu=80$ and $\sigma=15$, then $f_{y 1}(y), f_{y 2}(y), f_{y 3}(y)$ and $f_{y 4}(y)$ are all the Same - each is a normal pdf with $\mu=80$ and $\sigma=15$

The pdf describing an ordered observation, though ,is not the Same as the pdf describing a random observation. If a single observation is drawn from a normal distribution with $\mu=80$ and $\sigma=15$, it would not be surprising if that observation were to take on a value near 80 .

On the other hand, if $n=100$ observations is drawn. from that same distribution, we would not expect the smallest observation that is Y minto be anywhere. near 80 . common sense tells us that that smallest observation is likely to be much smaller than 80 , just as the largest observation , Y max, is likely to be much larger than 80.

## The Distribution of the Minimum:

Suppose that $X_{1}, X_{2}, \ldots X_{n}$ is a random sample from a continuous distribution with pdf $f$ and cdf $F$. We will now derive the pdf for $X_{(1)}$, the minimum value of the sample. For order statistics it is usually easier to begin by considering the cdf. The game plan will be to relate the cdf of the minimum to the behavior of the individual sampled values $X_{1}, X_{2}, \ldots . X_{n}$ for which we know the pdf and cdf.

## The cdf for the minimum $X_{(1)}$ is:

$$
\begin{aligned}
& F_{x_{(1)}}(x)=p\left(x_{(1)} \leq x\right) \\
& F_{x_{(1)}}(x)=p\left(x_{(1)} \leq x\right)=p\left(\text { at least one of } x_{1}, x_{2} \ldots \ldots x_{n} \text { is } \leq x\right) \\
& \begin{aligned}
& F_{x_{(1)}}(x)=p\left(x_{(1)} \leq x\right)=1-p\left(x_{(1)}>x\right) \\
&=1-p\left(x_{1}>x, x_{2}>x, \ldots \ldots \ldots x_{n}>x\right) \\
&= 1-p\left(x_{1}>x\right) p\left(x_{2}>x\right) \ldots \ldots \ldots\left(x_{n}>x\right) \\
&=1-[p(x>x)]^{n}=1-[1-p(x \leq x)]^{n} \\
& \quad=1-[1-f(x)]^{n}, \text { by independence }
\end{aligned}
\end{aligned}
$$

Take the derivative, we get the pdf for the minimum $X_{(1)}$ to be

$$
\begin{align*}
& f x_{(1)}(x)=\frac{d}{d x} f x_{(1)}(x)=\frac{d}{d x}\left\{1-[1-f(x)]^{n}\right\} \\
& =n[1-f(x)]^{n-1} f(x) \\
& f x_{(1)}(x)=n(1-f(x))^{n-1} f(x) \tag{1}
\end{align*}
$$

## Example (1):

Let $X_{1}, X_{2}, \ldots . X_{n}$ be independente random variables uniformly distributed on the interval [0.1]. complete the pdf of

$$
X_{(1)}=\min \left\{X_{1}, X_{2}, \ldots . X_{n}\right\}
$$

Solution: since
The CDF of x is:

$$
f(x)=\int_{-\infty}^{x} f(t) d t=\int_{0}^{x} 1 d t=\left.t\right|_{0} ^{x}=x
$$

So the pdf of $X_{(1)}$ is

$$
\begin{aligned}
f x_{(1)}(x) & =n(1-F x(x))^{n-1} f x(x) \\
& =n(1-x)^{n-1}
\end{aligned}
$$

This is the pdf for the beta distribution with parameters land $n$. Thus we can write $\quad X_{(1)} \sim \operatorname{Beta}(1, n)$

## Example (2):

Support $X_{1}, X_{2}, \ldots . X_{n}$ are iid exponential with mean $\beta>0$. Recall the exponential $(1 / \beta)$, the $\operatorname{pdf} f_{x}(x)$ is given by

$$
f_{x}(x)=\left\{\begin{array}{l}
\frac{1}{\beta} e^{-x / \beta, x>0} \\
0, \text { other wise }
\end{array}\right.
$$

Find the pdf of $X_{(1)}$, the minimum order statistics

## Solution:

The pdf of $X_{(1)}$, the minimum order statistics is

$$
\begin{gathered}
f_{X_{(1)}}(x)=n\left(1-F_{x}(x)\right)^{n-1} f x(x) \\
F x_{(x)}=\left\{\begin{array}{l}
0 \quad, x \leq 0 \\
1-e^{-x / \beta^{\prime}}, x>0
\end{array}\right. \\
f_{X_{(1)}}(x)=n\left(1-F_{x}(x)\right)^{n-1} f_{x}(x) \\
=n\left(\frac{1}{\beta} e^{-x / \beta}\right)\left[1-\left(1-e^{-x / \beta}\right)\right]^{n-1} \\
=\frac{n}{\beta} e^{-x / \beta}\left(e^{-x / \beta}\right)=\frac{n}{\beta}\left(e^{-x / \beta}\right)^{n}=\frac{n}{\beta} e^{-n x / \beta} \\
f x(1)(x)=\left\{\begin{array}{l}
\frac{n}{\beta} e^{-n x / \beta}, x>0 \\
0, \text { other wise }
\end{array}\right.
\end{gathered}
$$

There fore $X_{1}, X_{2}, \ldots X_{n} \sim \operatorname{iid} \operatorname{exponential}(1 / \beta) \rightarrow X_{(1)} \sim \operatorname{exponential}(n / \beta)$

## Example (3):

Let $X_{1}, X_{2}, \ldots X_{n}$ be independente exponential random variable with mean1 .compute the pdf of $X_{(1)}=\min \left\{X_{1}, X_{2}, \ldots X_{n}\right\}$

Solution: since

$$
f_{X_{(1)}}(x)=n\left(1-F_{X}(x)\right)^{n-1} f_{x}(x)
$$

The pdf of $x$ is

$$
f(x)=e^{-x}
$$

The CDF of x is:

$$
\begin{aligned}
& F(x)=\int_{-\infty}^{x} f(t) d t=\int_{0}^{x} e^{-t} d t=-\left.e^{-t}\right|_{0} ^{x}=1-e^{-x}, x>0 \\
& f_{X_{(1)}}(x)=n\left(1-F_{X_{1}}(x)\right)^{n-1} f x(x) \\
& =n\left(1-\left(1-e^{-x}\right)\right)^{n-1} e^{-x}=n e^{-n x} \quad \text { For } t>0 \text { and } 0 \text { other wise }
\end{aligned}
$$

## The Distribution of the Maximum:

Again consider our random sample $X_{1}, X_{2}, \ldots . X_{n}$ from a continuous distribution with pdf $f$ and cdf $F$. We will now derive the pdf for $X_{(n)}$, the maximum value of the sample. As with the minimum, we will consider the cdf and try to relate it to the behavior of the individual sampled values $X_{1}, X_{2}, \ldots . X_{n}$.

The cdf for the maximum $X_{(n)}$ is:

$$
\begin{aligned}
& F_{x_{(n)}}(x)=p\left(x_{n}\right.\leq x)=p\left(\max \left\{X_{1}, X_{2}, \ldots X_{n}\right\} \leq \mathrm{x}\right) \\
&=P\left(X_{1} \leq x, x_{2} \leq x, \ldots \ldots, x_{n} \leq x\right) \\
&=\left(x_{1} \leq x\right) p\left(x_{2} \leq x\right) \ldots \ldots p\left(x_{n} \leq x\right) \\
&=[p(x \leq x)]^{n}=[f(x)]^{n}, \text { by independence }
\end{aligned}
$$

Take the derivative, we get the pdf for the maximum $X_{(n)}$ to be

$$
\begin{align*}
& \quad f_{x_{(n)}}(x)=\frac{d}{d x} F x_{(n)}(x)=\frac{d}{d x}[F x(x)]^{n}=n[F(x)]^{n-1} f(x) \\
& f_{x_{(n)}}(x)=n[F x(x)]^{n-1} f x(x) \quad \ldots \ldots(2) \tag{2}
\end{align*}
$$

## Example (4):

let $X_{1}, X_{2}, \ldots X_{n}$ be independent random varibles uniformly distributed on the interval $[0,1]$. Compute. the pdf of $X_{(n)}=\max \left\{X_{1}, X_{2}, \ldots . X_{n}\right\}$

Solution: Since

$$
f_{x_{(n)}}(x)=n\left(F_{x}(x)\right)^{n-1} f_{x}(x)
$$

The CDF of x is :

$$
F(x)=\int_{-\infty}^{x} f(t) d t=\int_{0}^{x} 1 d t=\left.t\right|_{0} ^{x}=x
$$

So The pdf of $X_{(n)}$ is :

$$
\begin{aligned}
f_{x_{(n)}}(x)= & n\left(F_{x}(x)\right)^{n-1} f_{x}(x) \\
& =n x^{n-1}
\end{aligned}
$$

Which is the pdf of the Beta $(n, 1)$ distribution

## Example (5):

Suppose $X_{1}, X_{2}, \ldots X_{n}$ are iid exponential with mean $\beta>0$, recall the exponential $(1 / \beta)$, the $\operatorname{pdf} \mathrm{f}_{\mathrm{x}}(\mathrm{x})$ is given by

$$
f_{x}(x)=\left\{\begin{array}{l}
\frac{1}{\beta} e^{-x / \beta}, x>0 \\
0, \text { other wise }
\end{array}\right.
$$

Find the pdf of $X_{(n)}$, the maximum order statistics.

## Solution:

the pdf of $X_{(n)}$ the maximum order statistics is

$$
\begin{gathered}
f_{X_{(n)}}(x)=n\left(F_{X}(x)\right)^{n-1} f_{x}(x) \\
=n\left(1-e^{-x / \beta}\right)^{n-1}\left(1 / \beta e^{-x / \beta}\right)=\frac{n}{\beta} e^{-x / \beta}\left(1-e^{-x / \beta}\right)^{n-1} \\
\therefore f_{X_{(n)}}(x)=\int_{0}^{\frac{n}{\beta} e^{-x / \beta}\left(1-e^{-x / \beta}\right)^{n-1} \quad, x>0} \text { other wise }
\end{gathered}
$$

## The Joint Distribution of the Minimum and Maximum

Let's go for the joint cdf of the minimum and the maximum

$$
F_{X_{(1)}, X_{(n)}}(x, y)=p\left(X_{(1)} \leq x, X_{(n)} \leq y\right)
$$

It is not clear how to write this in terms of the individual $X_{i}$. Consider instead the relationship

$$
p\left(X_{(n)} \leq y\right)=p\left(X_{(1)} \leq x, X_{(n)} \leq y\right)+p\left(X_{(1)} \leq x, X_{(n)} \leq y\right) \ldots 1
$$

We know how to write out the term on the left-hand side. The first term on the right-hand side is what we want to compute. As for the final term,

$$
P\left(X_{(1)}>x, X_{(n)} \leq y\right)
$$

note that this is zero if $x \geq y$. (In this case , $P\left(X_{(1)}>x, X_{(n)} \leq y\right)=$ $P\left(X_{(n)} \leq y\right)$ and (1) gives us only $P\left(X_{(n)} \leq y\right)=P\left(X_{(n)} \leq y\right)$ which is both true and uninteresting! So, we consider the case that $x<y$. Note then that

$$
\begin{aligned}
P\left(X_{(1)}>x, X_{(n)} \leq y\right)= & P\left(x<X_{1} \leq y, x<X_{2} \leq y, \ldots \ldots, x<X_{n} \leq y\right) \\
& \underline{\underline{\mathrm{idd}}}\left[P\left(x<X_{1} \leq y\right)\right]^{n} \\
= & {[F(y)-F(x)]^{n} }
\end{aligned}
$$

Thus from (1), we have that

$$
\begin{aligned}
F_{X_{(1), X(n)}}(x, y) & =P\left(X_{(1)} \leq x, X_{(n)} \leq y\right) \\
& =P\left(X_{(n)} \leq y\right)-P\left(X_{(1)}>x, X_{(n)} \leq y\right) \\
& =[F(y)]^{n}-[F(y)-F(x)]^{n}
\end{aligned}
$$

Now the joint pdf is

$$
\begin{align*}
f_{X_{(1), X(n)}}(x, y) & =\frac{d}{d x} \frac{d}{d x}\left\{[F(y)]^{n}-[F(y)-F(x)]^{n}\right\} \\
& =\frac{d}{d x}\left\{n[F(y)]^{n-1} f(y)-n[F(y)-F(x)]^{n-1} f(y)\right\} \\
& =n(n-1)[F(y)-F(x)]^{n-2} f(x) f(y) . \tag{3}
\end{align*} \ldots \ldots(3)
$$

This hold for $\mathrm{x}<\mathrm{y}$ and for x and y both in the support of the original distribution.

For the sample of size 15 from the uniform distribution on $(0,1)$, the joint pdf for the min and max is

$$
f_{X(1), X(n)}(x, y)=15.14 .[y-x]^{13} I_{(0, y)}(x) I_{(0,1)}(y)
$$

A Heuristic:
Since $X_{1}, X_{2}, \ldots . X_{n}$ are assumed to come from a continuous distribution, the min and max are also continuous and the joint pdf does not represent
probability it is a surface under which volume represents probability. However, if we bend the rules and think of the joint pdf as probability, we can develop a heuristic method for remembering it.

Suppose (though it is not true) that

$$
f_{X_{(1)}, X_{(n)}}(x, y)=p\left(X_{(1)}=x, X_{(n)}=y\right)
$$

This would mean that we need one value in the sample $X_{1}, X_{2}, \ldots . X_{n}$ to fall at $x$, one value to fall at $y$, and the remaining $\mathrm{n}-2$ values to fall in between.

The "probability" one of the $X_{i}$ is $x$ is "like" $f(x)$. (Remember, we are bending the rules here in order to develop a heuristic. This probability is, of course, actually 0 for a continuous random variable.)

The "probability" one of the $X_{i}$ is $y$ is "like" $f(y)$.
The probability that one of the $X_{i}$ is in between $x$ and $y$ is (actually) $F(y)-F(x)$.

The sample can fall many ways to give us a minimum at x and a maximum at $y$. For example, imagine that $n=5$. We might get $X_{3}=x, X_{1}=y$ and the remaining $X_{2}, X_{4}, X_{5}$, in between $x$ and $y$.

This would happen with "probability"

$$
f(x)[F(y)-F(x)]^{3} f(y)
$$

Another possibility is that we get $\mathrm{X}_{5}=\mathrm{x}$ and $\mathrm{X}_{2}=\mathrm{y}$ and the remaining $\mathrm{X}_{1}, \mathrm{X}_{3}, \mathrm{X}_{4}$ in between x and $y$.

This would also happen with "probability"

$$
f(x)[F(y)-F(x)]^{3} f(y)
$$

We have to add this "probability" up as many times as there are scenarios. So, let's count them. There are 5! different ways to lay down the $X_{i}$. For each one, there are 3 ! different ways to lay down the remaining values in between that will result in the same min and max. So, we need to divide these redundancies out for a total of $5!/ 3!=(5)(4)$ ways to get that $\min$ at x and max at $y$.

In general, for a sample of size n , there are n ! different ways to lay down the $X_{i}$. For each one, there are ( $\mathrm{n}-2$ )! different ways that result in the same min and max. So, there are a total of $n!/(n-2)!=n(n-1)$ ways to get that

Thus, the "probability" of getting a minimum of $x$ and a maximum of $y$ is

$$
n(n-1) f(x)[F(y)-F(x)]^{n-2} f(y)
$$

which looks an awful lot like the formula we derived above!

## Example ( 6 ):

Consider 15 random variables $X_{1}, X_{2}, \ldots . X_{15}$ all having the $u[0,1]$ distribution . Find the joint pdf for the $\max$ and $\min$ statistics.

Solution: The pdf and cdf of the r.v. $X_{i}$ are

$$
\begin{aligned}
& f_{X_{i}}(x)=\left\{\begin{array}{ll}
1 & , 0 \leq x \leq 1 \\
0 & , \text { otherwise }
\end{array} \text { and } F_{X_{i}}(x)= \begin{cases}0 & , x \leq 0 \\
x & , 0 \leq x \leq 1 \\
1 & , x \geq 1\end{cases} \right. \\
& f_{X_{(1)}, X_{(n)}}(x, y)=n(n-1)[F(y)-F(x)]^{n-2} f(x) f(y) \\
&=15(14)(y-x)^{3}(1)(1) \\
&=210(y-x)^{3} \quad, 0<x<y<1
\end{aligned}
$$

## The Joint Distribution for All of the Order Statistics

We wish now to find the pdf

$$
f_{X_{(1)}}, x_{(2)}, \ldots \ldots, x_{n}\left(x_{1}, x_{2}, \ldots \ldots, x_{3}\right)
$$

This time, we will start with the heuristic aid.
Suppose that $n=3$ and we want to find

$$
f_{X_{(1)}}, x_{(2),}, x_{(3)}\left(x_{1}, x_{2}, x_{3}\right) "=\mathrm{P}\left(X_{(1)}=x_{1}, X_{(2)}=x_{2}, X_{(3)}=x_{3}\right) .
$$

The first thing to notice is that this probability will be 0 if we don't have $x_{1}<x_{2}<x_{3}$. (Note that we need strict inequalities here. For a continuous distribution, we will never see repeated values so the minimum and second smallest, for example, could not take on the same value.)

Fix values $x_{1}<x_{2}<x_{3}$. How could a sample of size 3 fall so that the minimum is $x_{1}$, the next smallest is $x_{2}$, and the largest is $x_{3}$ ? We could observe
$X_{1}=x_{1}, X_{2}=x_{2}, X_{3}=x_{3}$, or
$X_{1}=x_{2}, X_{2}=x_{1}, X_{3}=x_{3}$, or
$X_{2}=x_{2}, X_{2}=x_{3}, X_{3}=x_{1}$, or
There is 3 ! Possibilities to list. The "probability" for each is $f\left(x_{1}\right) f\left(x_{2}\right) f\left(x_{3}\right)$ thus,

$$
\begin{gathered}
f x_{(1)}, x_{(2),} x_{(3)}\left(x_{1}, x_{2}, x_{3}\right)=\mathrm{P} \mathrm{P}\left(X_{(1)}=x_{1}, X_{(2)}=x_{2}, X_{(3)}=x_{3}\right) \\
=3!f\left(x_{1}\right) f\left(x_{2}\right) f\left(x_{3}\right) .
\end{gathered}
$$

For general n, we have

$$
\begin{aligned}
f x_{(1)}, x_{(2)}, \ldots, x_{n}\left(x_{1}, x_{2}, \ldots, x_{n}\right) & = \\
& =" P\left(X_{(1)}=x_{1}, X_{(2)}=x_{2}, \ldots, X_{(n)}=x_{n}\right) \\
& =n!f\left(x_{1}\right) f\left(x_{2}\right) \ldots f\left(x_{n}\right)
\end{aligned}
$$

Which holds for $x_{1}<x_{2}<\cdots<x_{n}$ with all $x_{i}$ in the support for the original distribution. The joint pdf is zero otherwise.

The Formalities:
The joint cdf,
$\mathrm{P}\left(X_{(1)} \leq x_{1}, X_{(2)} \leq x_{2}, X_{n} \leq x_{n}\right)$.
is a little hard to work with. Instead, we consider something similar:

$$
P\left(y_{1}<X_{(1)} \leq x_{1}, y_{2}<X_{(2)} \leq x_{2}, \ldots ., y_{n}<X_{(n)}<x_{n}\right)
$$

For values $y_{1}<x_{1} \leq y_{2}<x_{2} \leq y_{3}<x_{3} \leq \cdots \leq y_{n}<x_{n}$.
This can happen if

$$
y_{1}<X_{1} \leq x_{1}, y_{2}<X_{2} \leq x_{2}, \ldots, y_{n}<X_{n}<x_{n}
$$

Or if

$$
y_{1}<X_{1} \leq x_{1}, y_{2}<X_{2} \leq x_{2}, \ldots, y_{n}<X_{n}<x_{n}
$$

Or...
Because of the constraints on the $x_{i}$ and $y_{i}$ these are disjoint events, So, we can add these n ! probabilities, which, will all be the same, together to get

$$
P\left(y_{1}<X_{(1)}<x_{1}, \ldots, y_{n}<X_{(n)}<x_{n}\right)=n!P\left(y_{1}<X_{1}<x_{1}, \ldots, y_{n}<X_{n}<x_{n}\right)
$$

Note that

$$
P\left(y_{1}<X_{1}<x_{1}, \ldots, y_{n}<X_{n}<x_{n}\right) \stackrel{i n d e p}{=} \prod_{i=1}^{n} P\left(y_{i}<X_{i} \leq x_{i}\right)=\prod_{i=1}^{n}\left[F\left(x_{i}\right)-F\left(y_{i}\right)\right] .
$$

So,

$$
P\left(y_{1}<X_{(1)}<x_{1}, \ldots, y_{n}<X_{(n)}<x_{n}\right)=n!\prod_{i=1}^{n}\left[F\left(x_{i}\right)-F\left(y_{i}\right)\right]
$$

The left -hand side is

$$
\int_{y_{n}}^{x_{n}} \int_{y_{n}-1}^{x_{n}-1} \ldots \int_{y_{1}}^{x_{1}} f x_{(1),} X_{(2)}, \ldots, X_{(n)}\left(u_{1}, u_{2}, \ldots, u_{n}\right) d u_{1} d u_{2} \ldots, d u_{n}
$$

Taking derivatives $\frac{d}{d x_{1}} \frac{d}{d x_{2}} \ldots \frac{d}{d x_{n}}$ gives

$$
f x_{(1)}, X_{(2)}, \ldots, X_{(n)}\left(x_{1}, x_{2}, \ldots, x_{n}\right)
$$

Differentiation both side of (2) with respect to $x_{1}, x_{2}, \ldots, x_{n}$ gives us
$f_{x_{(1)}, x_{(2)}, \ldots, x_{(n)}}\left(x_{1}, x_{2}, \ldots, x_{n}\right)=n!f\left(x_{1}\right) f\left(x_{2}\right) \ldots f\left(x_{n}\right)$
Which hold for $x_{1}<x_{2}<\cdots, x_{n}$ and all $X_{i}$ in the support of the original distribution. The pdf is zero otherwise.

## Example (7):

Let $X_{1}, X_{2}, X_{3}, X_{4}$ be a random sample from uniform distribution on the interval [0,5] if $y_{1}<y_{2}<y_{3}<y_{4}$
be the order statistic of the random sample $\left(x_{1}, x_{2}, \ldots, x_{4}\right)$
Find the joint pdf $\quad\left(y_{1}, y_{2}, \ldots, y_{4}\right)$
Solution: $\quad g\left(y_{1}, y_{2}, \ldots, y_{4}\right)=n!f\left(y_{1}\right), f\left(y_{2}\right), \ldots, f\left(y_{4}\right)$

$$
\begin{aligned}
& \text { since } f(x)=\frac{1}{b-a}=\frac{1}{5-0}=\frac{1}{5} \\
& g\left(y_{1}, y_{2}, \ldots, y_{4}\right)=4!f\left(y_{1}\right), f\left(y_{2}\right), \ldots, f\left(y_{4}\right) \\
&=24 \cdot \frac{1}{5} \cdot \frac{1}{5} \cdot \frac{1}{5} \cdot \frac{1}{5} \\
&=\frac{24}{625} \quad, 0<y_{1}<y_{2}<y_{3}<y_{4}<5
\end{aligned}
$$

## The Distribution of $\boldsymbol{X}_{(i)}$ :

We can get the marginal pdf for the ith order statistic $\boldsymbol{X}_{(i)}$, by taking the joint pdf for all order statistics from Section 5 and integrating out the unwanted $x_{i}$.
Let's start by integrating out $x_{1}$. Since the support of the joint pdf for the order statistics includes the constraint $x_{1}<x_{2}<\ldots<x_{n}$, limits of integration are $-\infty$ to $x_{2}$.

$$
\begin{aligned}
f_{X_{(2)}, \ldots X_{(n)}}\left(x_{2}, \ldots ., x_{n}\right)= & \int_{-\infty}^{x_{2}} f_{X_{(1)}, \ldots X_{(n)}},\left(x_{1}, \ldots . ., x_{n}\right) d x_{1} \\
& \left.=\int_{-\infty}^{x_{2}} n!f x_{(1)} f x_{(2)} \ldots . . f x_{(n)}\right) d x_{1} \\
& \left.=n!f x_{(2)} \ldots . . f x_{(n)}\right) \int_{-\infty}^{x_{2}} f\left(x_{1}\right) d x_{1} \\
& \left.=n!f x_{(2)} \ldots . . f x_{(n)}\right) F\left(x_{2}\right) d x_{1}
\end{aligned}
$$

for $x_{2}<x_{3}<\cdots<x_{n}$
Now lets integrate out $x_{2}$ which from $-\infty$ to $x_{3}$

$$
\begin{aligned}
& f_{X_{(3)}, \ldots X_{(n)}}\left(x_{3}, \ldots . ., x_{n}\right)=\int_{-\infty}^{x_{3}} f_{X_{(2)}, \ldots X_{(n)}},\left(x_{2}, \ldots \ldots, x_{n}\right) d x_{2} \\
& =n!f\left(x_{3}\right) \ldots . . f\left(x_{n}\right) \int_{-\infty}^{x 3} F\left(x_{2}\right) f\left(x_{2}\right) d x_{2} \\
& =n!f\left(x_{3}\right) \ldots . . f\left(x_{n}\right) \frac{1}{2}\left[F\left(x_{2}\right)\right]^{2} \left\lvert\, \begin{array}{c}
x_{(2)}=x_{(3)} \\
x_{(2)}=-\infty
\end{array}\right. \\
& =n!f\left(x_{3}\right) \ldots . . f\left(x_{n}\right) \frac{1}{2}\left(\left[F\left(x_{3}\right)\right]^{2}-[F(-\infty)]^{2}\right) \\
& =\frac{n!}{2} f\left(x_{3}\right) \ldots \ldots f\left(x_{n}\right)\left[F\left(x_{3}\right)\right]^{2}
\end{aligned}
$$

Which holds for $x_{3}<x_{4}<\cdots<x_{n}$
The next time through, we will integrate out $x_{3}$ from- $\infty$ to $x_{4}$. Using $u=F\left(x_{3}\right)$ and $d u=f\left(x_{3}\right) d x_{3}$, we get

$$
f_{X_{(4)}, \ldots X_{(n)}}\left(x_{4}, \ldots . ., x_{n}\right)=\frac{n!}{(3)(2)} f\left(x_{4}\right) \ldots . . f\left(x_{n}\right)\left[F\left(x_{4}\right)\right]^{3}
$$

Continue untilwe reach $X_{(i)}$ :

$$
f_{X_{(i)}, \ldots X_{(n)}}\left(x_{i}, \ldots \ldots, x_{n}\right)=\frac{n!}{(i-1)!} f\left(x_{i}\right) \ldots . . f\left(x_{n}\right)\left[F\left(x_{i}\right)\right]^{i-1}
$$

Which holds for $x_{i}<x_{i+1}<\cdots<x_{n}$
Now, we start integrating off $x$ is from the other side

$$
\left.\begin{array}{l}
\begin{array}{rl}
f_{X_{(i)}, \ldots X_{(n-1)}}\left(x_{i}, \ldots \ldots, x_{n-1}\right) & =\int_{x_{n-1}}^{\infty} f_{X_{(i)}, \ldots X_{(n-1)}}\left(x_{i}, \ldots, x_{n-1}\right) d x_{n} \\
& =\frac{n!}{(i-1)!} f\left(x_{i}\right) \ldots f\left(x_{n-1}\right)\left[F\left(x_{i}\right)\right]^{i-1} \int_{x_{n-1}}^{\infty} f\left(x_{n}\right) d x_{n} \\
& =\frac{n!}{(i-1)!} f\left(x_{i}\right) \ldots . . . f\left(x_{n-1}\right)\left[F\left(x_{i}\right)\right]^{i-1}\left[1-F\left(x_{n-1}\right)\right]
\end{array} \\
\text { for } x_{i}<x_{i+1}<\cdots<x_{n-1}
\end{array}\right\} \begin{aligned}
& f_{X_{(i)}, \ldots X_{(n-2)}\left(x_{i}, \ldots ., x_{n-2}\right)=\int_{x_{n-2}}^{\infty} f_{X_{(i)}, \ldots X_{(n-1)}}\left(x_{i}, \ldots, x_{n-1}\right) d x_{n-1}}^{\quad=\frac{n!}{(i-1)!} f\left(x_{i}\right) \ldots . . f\left(x_{n-2}\right)\left[F\left(x_{i}\right)\right]^{i-1} \int_{x_{n-2}}^{\infty} f\left(x_{n-1}\right)\left[1-F\left(x_{n-1}\right)\right] d x_{n-1}}
\end{aligned}
$$

Letting $u=\left[1-F\left(x_{n-1}\right)\right]$ and $d u=-f\left(x_{n-1}\right) d x_{n-1}$ we get
$f x_{i} \ldots . . x_{(n-2)}\left(x_{i}, \ldots, x_{n-2}\right)=\frac{n!}{(i-1)!} f\left(x_{i}\right) \ldots . . . f\left(x_{n-2}\right)\left[F\left(x_{i}\right)\right]^{i-1}\left\{-\frac{1}{2}\left[1-F\left(x_{n-1}\right)\right]^{2}\right\} \begin{aligned} & x_{n-1}=\infty \\ & x_{n-1}=x_{n-2}\end{aligned}$

$$
=\frac{n!}{2(i-1)!} f\left(x_{i}\right) \ldots . . f\left(x_{n-2}\right)\left[F\left(x_{i}\right)\right]^{i-1}\left[1-F\left(x_{n-2}\right)\right]^{2}
$$

$$
\text { for } x_{i}<x_{i+1}<\cdots<x_{n-2}
$$

The next time through, we will integrate out $x_{n-2}$ from $x_{n-3}$ to $\infty$.Note that

$$
\begin{gathered}
\int_{x_{n-3}}^{\infty} f\left(x_{n-2}\right)\left[1-F\left(x_{n-2}\right)\right]^{2} d x_{n-2}=-\frac{1}{3}\left[1-F\left(x_{n-2}\right)\right]^{3} \quad \begin{array}{l}
x_{n-2}=\infty \\
x_{n-2}=x_{n-3}
\end{array} \\
=\frac{1}{3}\left[1-F\left(x_{n-3}\right)\right]^{3}
\end{gathered}
$$

Thus

$$
f_{X_{(i)}, \ldots X_{(n-3)}}\left(x_{i}, \ldots . ., x_{n-3}\right)=\frac{n!}{(2)(3)(i-1)!} f\left(x_{i}\right) \ldots . . . f\left(x_{n-3}\right)\left[F\left(x_{i}\right)\right]^{i-1}\left[1-F\left(x_{n-3}\right)\right]^{3}
$$

for $\quad x_{i}<x_{i+1}<\cdots<x_{n-3}$

Continue all the way down to the marginal pdf for $X_{(i)}$ alone, we get

$$
f_{X_{(i)}}=\frac{n!}{(n-1)!(i-1)!}\left[F\left(x_{i}\right)\right]^{i-1} f\left(x_{i}\right)\left[1-F\left(x_{n-3}\right)\right]^{n-i}
$$

For $-\infty<X_{(i)}<\infty\left(\leftarrow\right.$ this may be further restricted by indicators in $f\left(x_{i}\right)$

Theorem (1): Let $Y_{1}, Y_{2}, \ldots, Y_{n}$ be a random sample of continuous random variables drawn from a distribution having pdf $f_{Y}(y)$ and $\operatorname{cdf} F_{Y}(y)$. The pdf of the ith order statistic is given by

$$
f_{Y_{i}}(y)=\frac{n!}{(n-1)!(i-1)!}\left[F_{Y}(y)\right]^{i-1}\left[1-F_{Y}(y)\right]^{n-i} f_{Y}(y)
$$

For $1 \leq i \leq n$.
Proof We will give a heuristic argument that draws on the similarity between the statement of Theorem (1) and the binomial distribution. For a formal induction proof verifying the expression given for $f_{Y}(y)$.
Recall the derivation of the binomial probability function,
$p_{x}(k)=P(X=k)=\binom{n}{k} p^{k}(1-p)^{n-k}$, where X is the number of successes in n independent trials, and p
is the probability that any given trial ends in success. Central to that derivation was the recognition that the event " $X=k$ " is actually a union of all the different (mutually exclusive) sequences having exactly $k$ successes and $n-k$ failures. Because the trials are independent, the probability of any such sequence is $\mathrm{p}^{\mathrm{k}}(1-\mathrm{p})^{\mathrm{n}-\mathrm{k}}$ and the number of such sequences is $n!/[k!(n-k)!]\left(\operatorname{or}\binom{n}{k}\right)$.
probability that $X=k$ is the product $\binom{n}{k} \mathrm{p}^{\mathrm{k}}(1-\mathrm{p})^{\mathrm{n}-\mathrm{k}}$

Here we are looking for the pdf of the $i$ th order statistic at some point $y$ that is $f_{Y}(y)$. As was the case with the binomial, that pdf will reduce to a combinatorial term times the probability associated with an intersection of independent events The only fundamental difference is that $Y_{i}$ is a continuous
random variable, whereas the binomial X is discrete, which means that what we find here will be a probability denstry function.

$$
\begin{equation*}
f_{Y_{i}}(y)=\frac{n!}{(n-1)!(i-1)!}\left[F_{Y}(y)\right]^{i-1}\left[1-F_{Y}(y)\right]^{n-i} f_{Y}(y) \tag{5}
\end{equation*}
$$

## Example (8):

Let $\mathrm{Y}_{1}<\mathrm{Y}_{2}<\mathrm{Y}_{3}<\mathrm{Y}_{4}$ denote the order statitics on of a random samples of size (4) from a distribution having the following

$$
\begin{aligned}
& \text { p.d.f } \\
& \mathrm{f}(\mathrm{x})=\left[\begin{array}{cc}
2 x & 0<x<1 \\
0 & \text { o.w }
\end{array}\right.
\end{aligned}
$$

Find the p.d.f of $y 3$
Solution : $n=4$ and $i=3$

$$
\begin{aligned}
& g\left(Y_{i}\right)=\frac{n!}{(i-1)!(n-i)!}\left[F\left(y_{i}\right)\right]^{i-1}\left[1-F\left(y_{i}\right)\right]^{n-i} F\left(y_{i}\right) \\
& g\left(y_{3}\right)=\frac{4!}{2!1!}\left[F\left(y_{3}\right)\right]^{2}\left[1-F\left(y_{3}\right)\right]^{1} f\left(y_{3}\right) \\
& F\left(y_{3}\right)=\int_{0}^{y_{3}} f(u) d u=\int_{0}^{y_{3}} 24 d u=4^{2} \mathrm{I}_{0}^{y_{3}}=y_{3}^{2} \\
& g\left(y_{3}\right)=12\left(\mathrm{y}_{3}^{2}\right)^{2} \cdot\left(1-\mathrm{y}_{3}^{2}\right)^{1} \cdot 2 y_{3}=24 \mathrm{y}_{3}^{5}\left(1-\mathrm{y}_{3}^{2}\right) \\
& \therefore g\left(y_{3}\right)=24 \mathrm{y}_{3}^{5} \cdot\left(1-\mathrm{y}_{3}^{2}\right) \quad 0<y_{3}<1
\end{aligned}
$$

The Joint Distribution of $X_{(i)}$ and $X_{(j)}$ for $i<j$
The joint pdf for all of the order statistics and integrate out The result will be .
$f x_{(i),} X_{j}\left(x_{j}, x_{j}\right)=\frac{n!}{(i-1)!(j-i-1)!(n-j)!}[F(x i)]^{i-1} f(x i)[F(x i)]^{j-i-1} f(x i)[1-$
$F(x j)]^{n-j}$.....(6)
for $-\infty<x_{i}<x_{j}<\infty$

## Example (9):

Let $\mathrm{X}_{(1)}<\mathrm{X}_{(2)}<\mathrm{X}_{(3)}<\mathrm{X}_{(4)}<\mathrm{X}_{(5)} \quad$ be order statistics on of a random samples of size 5 from a distribution having probability density function

$$
f(x)=\left\{\begin{array}{cl}
2 x & , 0<x<1 \\
0 & , \text { otherwise }
\end{array}\right.
$$

Find the joint pdf of $X_{(2)}$ and $X_{(4)}$

## Solution :

$f_{X_{(i)}, X_{(j)}}\left(x_{i}, x_{j}\right)=\frac{n!}{(i-1)!(j-i-1)!(n-j)!}\left[F\left(x_{i}\right)\right]^{i-1} f\left(x_{i}\right)\left[F\left(x_{j}\right)-F\left(x_{i}\right)\right]^{j-i-1} f\left(x_{j}\right)\left[1-F\left(x_{j}\right)\right]^{n-j}$

$$
\begin{aligned}
f_{X_{(2)}, X_{(4)}}\left(x_{2}, x_{4}\right) & =\frac{5!}{1!1!1!}\left[x_{2}^{2}\right]\left[x_{4}^{2}-x_{2}^{2}\right]\left[1-x_{4}^{2}\right]\left(2 x_{2}\right)\left(2 x_{4}\right) \\
& =480\left[x_{2}^{3}\right]\left[x_{4}\right]\left[x_{4}^{2}-x_{2}^{2}\right]\left[1-x_{4}^{2}\right], \quad 0<x_{2}<x_{4}<1
\end{aligned}
$$

## References :

1. Border, K. C, (lecture15:Orders Statistics, Conditional Expectations), Introduction to probability and Statistics, Department of Mathematics, p. 1-22, 2021.
2. kschischang, F.R. (Order Statistics), 2019.
3. Mohammed, A.T, (lectures on mathematical statistics), university of Baghdad, 2022.
4. Sheffield, S. , (Conditional probability, Order Statistics, expectations of Sums).
5. Tsun, A., (Chapter 5,Multiple Random Variables), 5.10: Order Statistics, probability and Statistics with Applications to Computing 5.10, p.1-5.
6. https: academics. Su.edu. krd (order Statistics Definition)
7. https:// www.colorado.edu (order statistics 1 Introduction and Notation)
8. .http:// www.math.ntu.edu.tw(Order Statistics. Chapter 2)
9. http:// www.maths.dur.ac.uk (order Statistics)
10. http://www2 .stat.duke.edu (lecture 15: order statistics)
