AUA CS108, Statistics, Fall 2020 Lecture 12

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23 Sep 2020

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- ▶ 75% of Datapoints are to the left of the Upper Quartile Q_3 , and 25% are to the right, so Q_3 divides the (sorted) Dataset in the (approximate) proportion 75%-25%

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Now, let $\alpha \in (0,1)$. We want to find a real number q_{α} dividing our (sorted) Dataset into the proportion $100\alpha\% - 100(1-\alpha)\%$, i.e., q_{α} is a point such that the α -portion of the Datapoints are to the left to q_{α} , and others are to the right.

Let $x: x_1, x_2, ..., x_n$ be our 1D numerical Dataset. Assume also that $\alpha \in (0,1)$.

Definition: The Quantile of order α (or $100\alpha\%$ order, the α -Quantile) of x is defined by

$$q_{\alpha} = q_{\alpha}^{\mathsf{x}} = \mathsf{x}_{([\alpha \cdot \mathsf{n}])}.$$

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Note: There are different definitions of the α -quantile in the literature and in software implementations. Say, **R** has 9 methods to calculate quantiles.

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Note: Sometimes Quantiles are called Percentiles.

Example

Example: Find the 20% and 60% quantiles of

$$x: -2, 3, 5, 7, 8, -3, 4, 5, 2$$

Solution: OTB

Example

```
Now, let us calculate Quantiles in {\bf R}:
```

2.4 5.2 10.8

```
x <- 1:15
quantile(x,0.21)

## 21%
## 3.94
quantile(x, c(0.1,0.3,0.7))

## 10% 30% 70%</pre>
```

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$$F(q_{\alpha}) = \alpha,$$
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If F has a Density, f(x), then q_{α} can be calculated from

$$\int_{-\infty}^{q_{\alpha}} f(x) dx = \alpha.$$

Theoretical Quantiles, Geometrically, by CDF

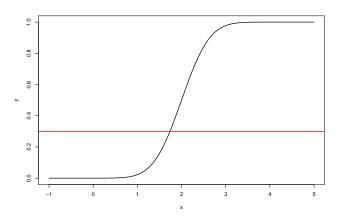
First we draw the CDF y = F(x) graph, then draw the line $y = \alpha$.

Theoretical Quantiles, Geometrically, by CDF

First we draw the CDF y=F(x) graph, then draw the line $y=\alpha$. Now, we keep the portion of the graph of y=F(x) above (or on) the line $y=\alpha$. Then we take the leftmost point of the remaining part, and the x-coordinate of that point will be q_{α} .

Theoretical Quantiles, Geometrically, by CDF

```
alpha <- 0.3
x <- seq(-1,5, by = 0.01)
y <- pnorm(x, mean = 2, sd = 0.5)
plot(x,y, type = "l", xlim = c(-1,5), lwd = 2)
abline(h = alpha, lwd = 2, col = "red")</pre>
```



Theoretical Quantiles, Geometrically, by PDF

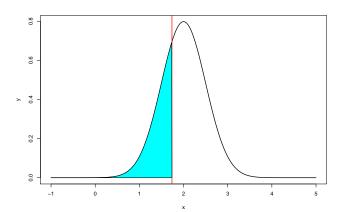
Now, assume our Distribution is continuous. We plot the graph of the PDF y = f(x).

Theoretical Quantiles, Geometrically, by PDF

Now, assume our Distribution is continuous. We plot the graph of the PDF y=f(x). We take q_{α} to be the smallest point such that the area under the PDF curve **left to** q_{α} is exactly α .

Theoretical Quantiles, Geometrically, by PDF alpha <- 0.3; q.alpha <- qnorm(alpha, mean = 2, sd = 0.5) x <- seq(-1,5, by = 0.01)

```
y <- dnorm(x, mean = 2, sd = 0.5)
plot(x,y, type = "l", xlim = c(-1,5), lwd = 2)
abline(v = q.alpha, lwd = 2, col = "red")
polygon(c(x[x<=q.alpha], q.alpha),c(y[x<=q.alpha],0),col="cyan")</pre>
```



Examples

Example: Find the 30% quantile of Unif[3, 10]

Solution: OTB

Examples

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Solution: OTB

Example: Find the 70% quantile of the Distribution with the PDF

$$f(x) = \begin{cases} 3x^2, & x \in [0, 1] \\ 0, & otherwise \end{cases}$$

Solution: OTB

Now, if q_{α} is the α -quantile of some Distribution, and X is a r.v. from that Distribution, then

$$\mathbb{P}(X \leq q_{\alpha}) \geq \alpha$$
 and $\mathbb{P}(X \geq q_{\alpha}) \geq 1 - \alpha$.

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Note: Here we are taking inequalities, and not, say, $\mathbb{P}(X \leq q_{\alpha}) = \alpha$, since, in the Discrete r.v. case, we can have no q_{α} with exact equality. Say, if $X \sim Bernoulli(0.2)$, and $\alpha = 0.4$, then no q_{α} exists with $\mathbb{P}(X \leq q_{\alpha}) = \alpha$.

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Note: If $\alpha=0.5$, we call $q_{\alpha}=q_{0.5}$ to be the **Median of the Distribution**. So if we consider a Continuous r.v. and draw the PDF of that r.v., then the Median is the (leftmost) point dividing the area under the PDF curve into 50%-50% portions.