## RANDOM VARIABLE and its CHARACTERISTICS

## Visualizing Random Variable

suppose we have 3000 numerical values. All these data follow a certain distribution - behave in a specific manner. In order to depict this behaviour we may construct a

Histogram


## Histogram

the horizontal axis are the intervals ('bins') our values belong to. The range is (practically) from 2 to 9.5 . And this range has been divided into 15 bins:

| 2-2.5 | 2.5-3 | 3-3.5 | 3.5-4 | 4-4.5 | 4.5-5 | 5-5.5 | 5.5-6 | 6-6.5 | 6.5-7 | 7-7.5 | 7.5-8 | 8-8.5 | 8.5-9 | 9-9.5 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 5 | 15 | 60 | 132 | 287 | 455 | 583 | 545 | 435 | 275 | 141 | 45 | 20 | 2 | 2 |

The second row shows how many values belong to a given interval: e.g. the third entry 60 shows that sixty values are greater than 3.0 and equal to or less than 3.5. In the given bin we have thus 60 out of 3000 .
The probability that our RV $X$ has the values: $3.0<x \leq 3.5$ is $60 / 3000=0.002$. The height of the vertical bar is the measure of this probability.
But for practical reasons we have to depict distributions with numbers rather than graphs. $\because$

## A FUNCTION OF A RANDOM VARIABLE: $Y=H(X) \ldots$

is also a random variable - so it also has - $F(y)$ a cumulative distribution with some PARAMETERS (which may be known from an experiment)

MATHEMATICAL EXPECTATION or the MEAN VALUE OF A RANDOM VARIABLE

$$
E(X)=\hat{x}= \begin{cases}\sum_{k=0}^{n} x_{k} \mathcal{P}\left(X=x_{k}\right)=\sum_{k=0}^{n} p_{k} x_{k} & \text { for a discrete RV } \\ \int_{-\infty}^{\infty} x f(x) d x & \text { for a continuous RV }\end{cases}
$$

## remember. . .

... every mathematical expectation is a number, so $E(X)$ is no longer something which may be called 'random'.
We use various conventions of notation: $E(X), \hat{x}, \mu$ (the 'true' mean value for the given RV $X$ ) and $m$ (the estimated mean value for the given $X$ ).
For a physicist (well, not only) $E(X)$ may be perceived as a "centre-of-mass" of the $X$, or ...
weighted mean: $E(X)=\sum w_{i} x_{i} / \sum w_{i}$.
The weights are:
$p_{i}$ 's for discrete RV $-E(X)=\sum p_{i} x_{i}$
and $f(x) d x=\mathcal{P}(X \in[x, x+d x])$ for continuous RV
In the second case the sum is of course replaced by an integral.

$$
E(X)=\int_{-\infty}^{\infty} x \cdot f(x) d x
$$

## MOMENTS OF RANDOM VARIABLES

Let our function of the random variable V Be:

$$
H(X)=(X-c)^{l}
$$

( $c$-ANY NUMBER); ITS MATHEMATICAL EXPECTATION

$$
E\left\{(X-c)^{l}\right\}
$$

IS CALLED THE $l$-TH MOMENT OF THE RANDOM variable $X$ with RESPECT TO $c$.

$$
\alpha_{l} \stackrel{\text { def }}{=} E\left\{(X-c)^{l}\right\}
$$

It is a logical to put $c=E(X)(\hat{x})$ - in this manner we obtain the so-called CENTRAL MOMENTS:

$$
\mu_{l}=E\left\{(X-\hat{x})^{l}\right\}
$$

## MOMENTS OF RANDOM VARIABLES, cntd.

Let's consider the case of a continuous variable:

$$
\begin{aligned}
& \mu_{0}=\int_{-\infty}^{\infty}(x-\hat{x})^{0} f(x) d x=1 \\
& \mu_{1}=\int_{-\infty}^{\infty}(x-\hat{x})^{1} f(x) d x=0 \\
& \mu_{2}=\int_{-\infty}^{\infty}(x-\hat{x})^{2} f(x) d x \stackrel{\text { def }}{=} \operatorname{VAR}(X)=\sigma^{2}(X)=\text { VARIANCE } \\
& \mu_{3}=\int_{-\infty}^{\infty}(x-\hat{x})^{3} f(x) d x=\text { SKEWNESS } \\
& \mu_{4}=\int_{-\infty}^{\infty}(x-\hat{x})^{4} f(x) d x=\text { KURTOSIS }
\end{aligned}
$$

## MOMENTS OF RANDOM VARIABLES, cntd.

what is the meaning od those moments?

- VARIANCE - a measure of the spread (dispersion) (always $>0$ )
- SKEWNESS - a measure of asymmetry
- KURTOSIS - a measure of the spread as compared with a special type of distribution - normal distribution

$$
\sigma=\sqrt{V A R(X)}=\sigma(X)=\sigma_{x}
$$

- Standard mean deviation of a random variable X N.B. it is expressed in the same UNITS as X!


## $\sigma(X) \ldots$

... may be regarded as a natural unit for measuring our Random Variable.

## a short-cut formula for calculating the variance:

$$
[X-E(X)]^{2}=X^{2}-2 E(X) X+[E(X)]^{2} \quad \star
$$

but we have ( $X$ - a R.V.; $a, b$ - constants)

$$
E(a X+b)=a E(X)+b
$$

proof (for a discrete-type R.V)

$$
\sum_{i} p_{i} x_{i}=\sum_{i} p_{i}\left(a x_{i}+b\right)=a \sum_{i} p_{i} x_{i}+b \sum_{i} p_{i}=a E(X)+b
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(Repeat this proof for the case of a continuous RV.)

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$$

(Repeat this proof for the case of a continuous RV.)
Applying the $E$ operator to the right member of the equation $\star$

$$
E\left(X^{2}\right)-2 E(X) E(X)+E\left\{[E(X)]^{2}\right\}=E\left(X^{2}\right)-[E(X)]^{2}
$$

One may prefer the so-called standardised parameters

$$
\begin{aligned}
& \gamma_{3}=\frac{\mu_{3}}{\sigma^{3}}(=\gamma) \\
& \gamma_{4}=\frac{\mu_{4}}{\sigma^{4}}-3=\frac{\mu_{4}}{\mu_{2}^{2}}-3 \\
& \gamma_{3}>0 \rightarrow E(X)-M o>0
\end{aligned}
$$

$\gamma_{4}>0 \rightarrow$ the distribution is ,,slimmer" than the Normal distribution

$$
Z=\frac{X-\hat{x}}{\sigma}
$$

$\hat{x}$ - is a "natural" zero (origin)
$\sigma$ - is a "natural" unit

Let $X$ be a RV with $E(X)=\hat{x}$ and $V A R(X)=\sigma^{2}$. Then, for $d$ being a number:

$$
\mathcal{P}(|X-\hat{x}| \geq d) \leq \frac{\sigma^{2}}{d^{2}}, \quad \text { or }
$$

$$
\text { putting: } d=k \cdot \sigma \quad \text { we get } \quad \mathcal{P}(|X-\hat{x}| \geq k \cdot \sigma) \leq \frac{1}{k^{2}} .
$$

This is CHEBYSHEV INEQUALITY - a rather crude estimate of the dispersion of our $X$ around $E(X)$.

## DESCRIPTIVE STATISTICS

- quantile:

A QUANTILE $q(f)$ or $x_{f}$, is a value of $x$ for which a specified fraction, $f$, of the X values is less than or equal to $x_{f}$ :

$$
\begin{align*}
F\left(x_{f}\right) & =\mathcal{P}\left(X \leq x_{f}\right) \geq f  \tag{1}\\
1-F\left(x_{f}\right) & =\mathcal{P}\left(X>x_{f}\right) \leq 1-f \tag{2}
\end{align*}
$$

(for a continuous RV we have the " $\geq$ " or " $\leq$ " sign)
QUANTILE for $f=0.5$ (50\%) is called median; for $f=0.25$ ( $25 \%$ ) we have the first (lower) quartile, and for $f=0.75$ ( $75 \%$ ) we have the fourth (upper) quartile

- MODE (modal value - $\operatorname{Mo}(X)$ )
is a value $x$, for which: $\frac{d f}{d x}=0$ and $\left.\frac{d^{2} f}{d x^{2}} \right\rvert\,<0$
- (local maximum of the probability density function)
- RANGE: $\quad x_{\max }-x_{\min }$


## DESCRIPTIVE STATISTICS

## Box-and-whiskers plot

values taken over by random variable $X$

after Jacek Tarasiuk "Wykłady ze statystyki inżynierskiej" WFilS 2013

## DESCRIPTIVE STATISTICS





