

$g: \text{one-to-one from } (a, b) \rightarrow (c, d)$
 $\uparrow \quad \quad \quad \uparrow$
 $x \quad \quad \quad y = g(x)$

$$\underline{f_y(y) = f_x(g^{-1}(y)) \left| \frac{d}{dy} g^{-1}(y) \right| \mathbb{1}(y \in (c, d))}$$

COVT as discussed is for 1-1 functions

$\boxed{y = x^2}$ and x can take both +ve and -ve values

$g(x) = x^2$ not 1-1 in $(-\infty, \infty)$

Theorem 2.5 Let $y = g(x)$

$P(\underline{x} \in B) = 1$ for some open set B .

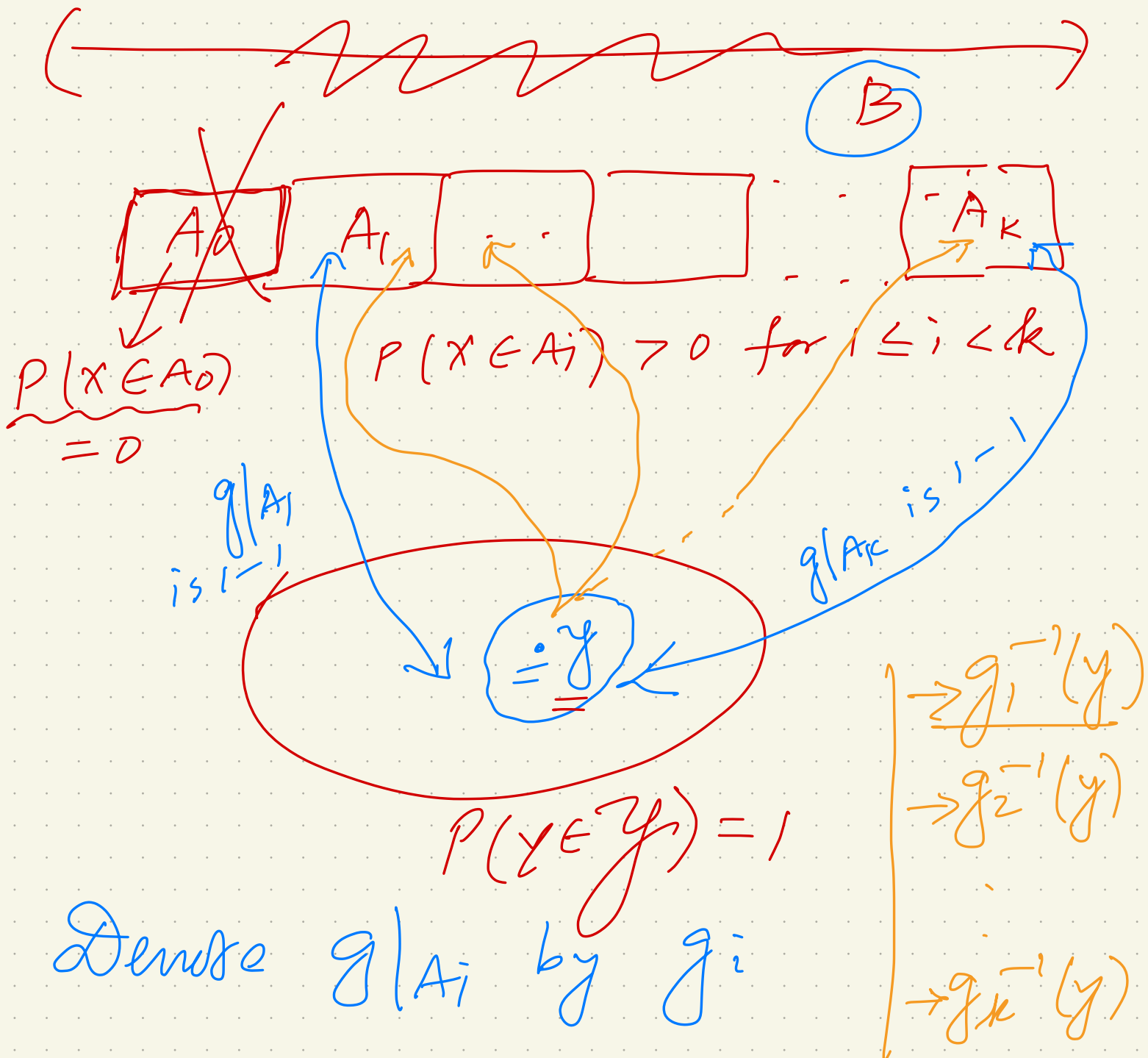
Let y be such that $P(\underline{y} \in \underline{y}) = 1$

Suppose there is a partition

(A_0, A_1, \dots, A_k) of B with

$$P(x \in A_0) = 0,$$

and such that $g|_{A_i}$ is a 1-1 continuously differentiable function between A_i and Y with non-vanishing derivative.



Then

$$f_Y(y) = \sum_{i=1}^k f_X(g_i^{-1}(y)) \left| \frac{d}{dy} g_i^{-1}(y) \right|$$

Another extension.

When Y itself can be partitioned.

Now assume that apart from a set which has probability 0 under the distribution of Y ,

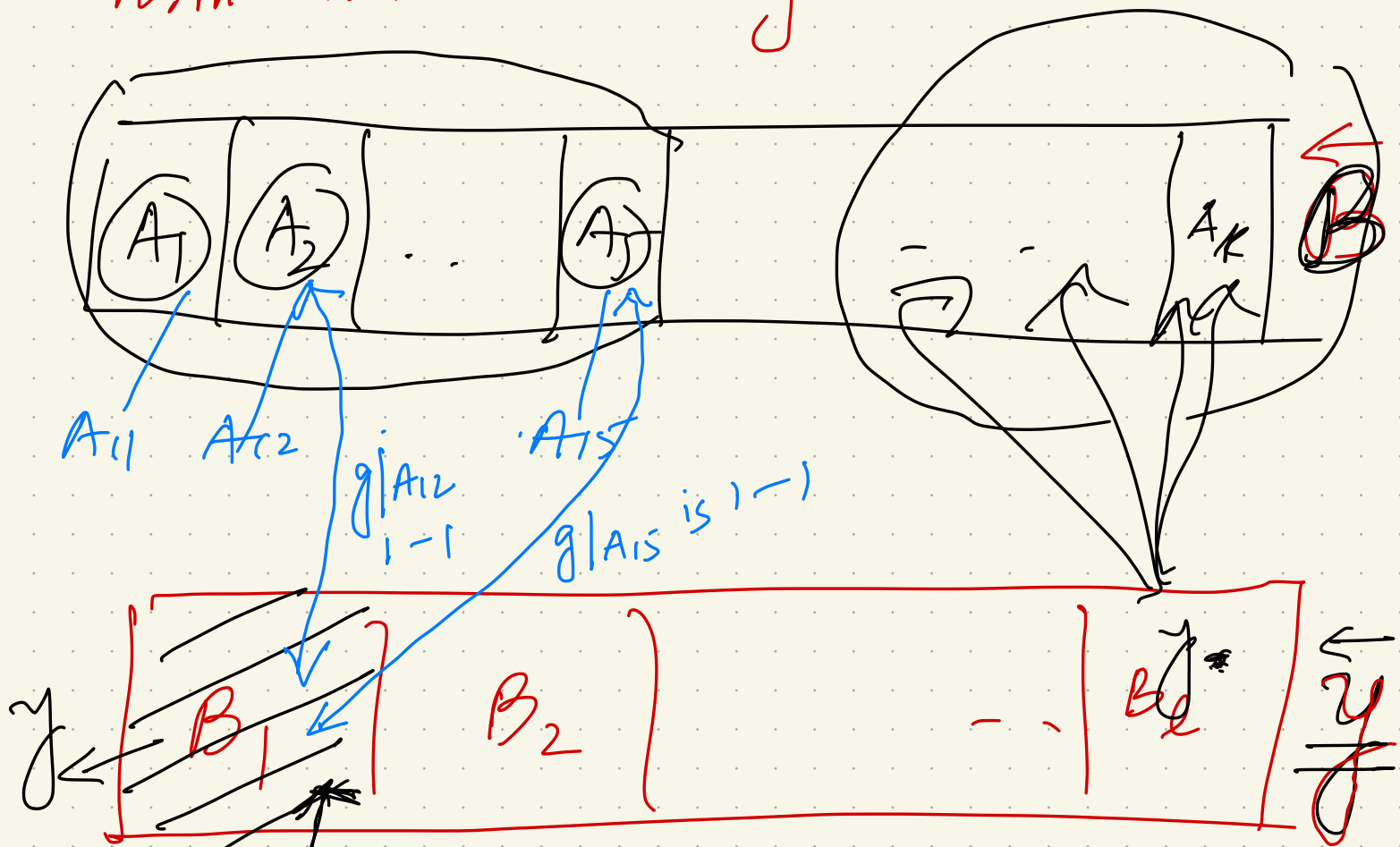
$Y = B_1 \cup B_2 \dots \cup B_\ell$ where this is a partition, and suppose that

for each B_j , there's a subcollection

$\{A_{ij}\}$ of $\{A_1, A_2, \dots, A_k\}$

with $g|_{A_{ij}}$ being 1-1 from A_{ij} to B_j

and nicely continuously differentiable
with non vanishing derivative.



$$f_y(\underline{y}) =$$

$$\sum_{\underline{A_{ij}}} \frac{f_x(g_{ij}^{-1}(y))}{\left| \frac{d}{dy} g_{ij}^{-1}(y) \right|}$$

if $y \in B_i$

Exercise:

2.6 (i) $Y = X^2$, $X \sim N(0, 1)$

Find f_Y .

$$f_X(x) = \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{x^2}{2}\right], x \in \mathbb{R}$$

$g(x) = x^2$ is NOT 1-1!

Apply 2.5, with $Y = (0, \infty)$

($P(Y \in Y) = 1$) and with $A_0 = \{0\}$

$$A_1 = (0, \infty), A_2 = (-\infty, 0).$$

$$P(X \in A_0) = 0$$

$g|_{A_1}$ is 1-1 from $(0, \infty)$ to $(0, \infty)$

$g|_{A_2}$ is 1-1 from $(-\infty, 0)$ to $(0, \infty)$.

Consider $y \in \mathcal{Y}$, $y > 0$.

$$f_Y(y) = \underbrace{f_X(g_1^{-1}(y)) \left| \frac{d}{dy} g_1^{-1}(y) \right|}_{1^{st} \text{ term}} + \underbrace{f_X(g_2^{-1}(y)) \left| \frac{d}{dy} g_2^{-1}(y) \right|}_{2^{nd} \text{ term}}.$$

$$g_1: \underline{(0, \infty)} \rightarrow \underline{(0, \infty)} \text{ with } g_1(x) = x^2$$

$$g_2: \underline{(-\infty, 0)} \rightarrow \underline{(0, \infty)} \text{ with } g_2(x) = x^2$$

$$2^{nd} \text{ term: } g_2^{-1}(y) = -\sqrt{y}$$

$$\frac{d}{dy} g_2^{-1}(y) = \underline{-\frac{1}{2\sqrt{y}}}$$

So, 2nd term:

$$\frac{1}{\sqrt{2\pi}} \exp \left[-\frac{1}{2} (-\sqrt{y})^2 \right] \frac{1}{2\sqrt{y}}$$

$$= \frac{1}{\sqrt{2\pi}} e^{-\frac{y}{2}} \frac{1}{2\sqrt{y}} \left. \vphantom{\frac{1}{\sqrt{2\pi}}} \right\} \begin{array}{l} \text{equals} \\ 1^{st} \\ \text{term} \end{array}$$

So, finally:

$$f_Y(y) = \frac{1}{\sqrt{2\pi} \sqrt{y}} \exp\left(-\frac{y}{2}\right) \mathbb{1}(y > 0)$$

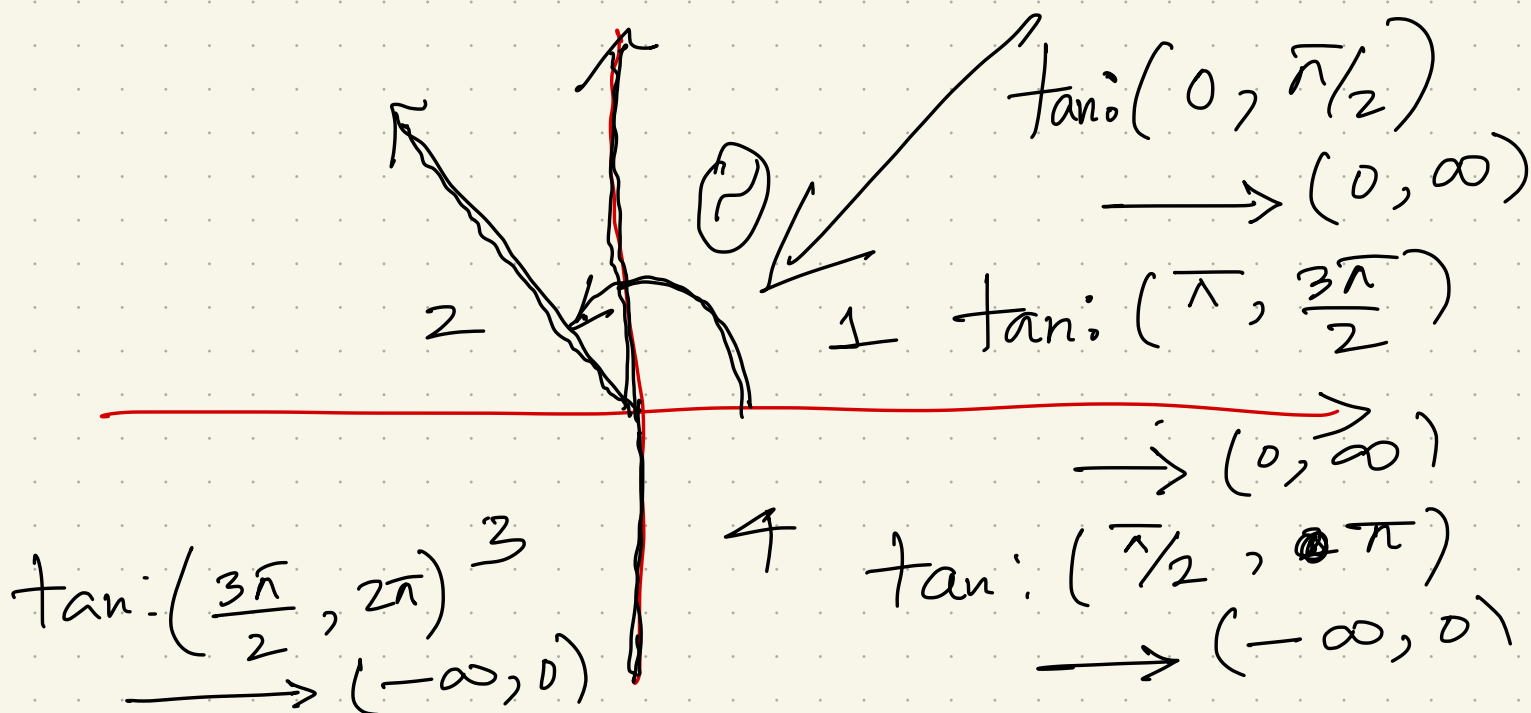
χ^2_1 density or a $\Gamma(1/2, 1/2)$

application of the further extension:

$\Theta \sim \text{Uniform on } (0, 2\pi)$.

$Y = \tan(\Theta)$. Find dist. of Y .

$$f_{\Theta}(\theta) = \frac{1}{2\pi} \mathbb{1}(0 < \theta < 2\pi)$$



A's

$$\left(0, \frac{\pi}{2}\right) \cup \left(\frac{\pi}{2}, \pi\right) \cup \left(\pi, \frac{3\pi}{2}\right) \cup \left(\frac{3\pi}{2}, 2\pi\right)$$

Arrows labeled $\tan^{(1)}$ and $\tan^{(2)}$ point from the intervals to the corresponding intervals in B's.

B's: $\left(0, \infty\right) \cup \left(-\infty, 0\right)$

Arrows labeled $\tan^{(1)}$ and $\tan^{(2)}$ point from the intervals to the corresponding intervals in B's.

Take $y > 0$

$$f_y(y) = \left[\frac{f_\theta(\tan^{(1)-1}(y))}{\left| \frac{d}{dy} \tan^{(1)-1}(y) \right|} + \frac{f_\theta(\tan^{(2)-1}(y))}{\left| \frac{d}{dy} \tan^{(2)-1}(y) \right|} \right]$$

Check
same
expression
holds
for $y < 0$

$$= \frac{1}{2\pi} \frac{1}{1+y^2} + \frac{1}{2\pi} \frac{1}{1+y^2} = \frac{1}{\pi(1+y^2)}$$

Conclude:

$$f_Y(y) = \frac{1}{\pi} \frac{1}{1+y^2} \mathbb{1}(y \in \mathbb{R})$$

Cauchy \checkmark density or t_1 density.

Section 3

X \rightarrow typically a low dimensional
r.v. function (functional) is
of interest.

A measure of centrality.

central tendency.

Average / Expectation.

$$\{ \underline{x_1}, \underline{x_2}, \dots, \underline{x_n} \} \quad \text{Avg}(x_i\text{'s})$$
$$= \left\{ \frac{x_1 + \dots + x_n}{n} \right\}$$

X : assumes values

$$\{ \underline{x_1}, \underline{x_2}, \dots \}$$

Let $\underline{p(x_j)} = P(X = x_j)$

$$E[g(x)] = \sum_{j=1}^{\infty} g(x_j) p(x_j)$$

provided $E[g(x)] < \infty$

$$E[g(x)] = \sum g(x_j) p(x_j)$$

X is continuous with p.d.f $f(x)$,

then

$$E[g(x)] = \int_{\mathbb{R}} g(x) f(x) dx$$

provided $\left[\int_{\mathbb{R}} |g(x)| f(x) dx \right] < \infty.$

$$E[|g(x)|]$$



To define expectations:

First define $E(x)$ for any non-negative random variable.

For any general Y , write

$$Y = Y^+ - Y^-$$

$$Y^+ = Y \mathbb{1}(Y \geq 0)$$

$$Y^- = -Y \mathbb{1}(Y < 0)$$

$$|y| = y^+ + y^-$$

$$y = y^+ - y^-$$

We want to write

$$Ey = Ey^+ - Ey^-$$

Basically makes sense when both

are finite

will require Ey^+ and Ey^- to be

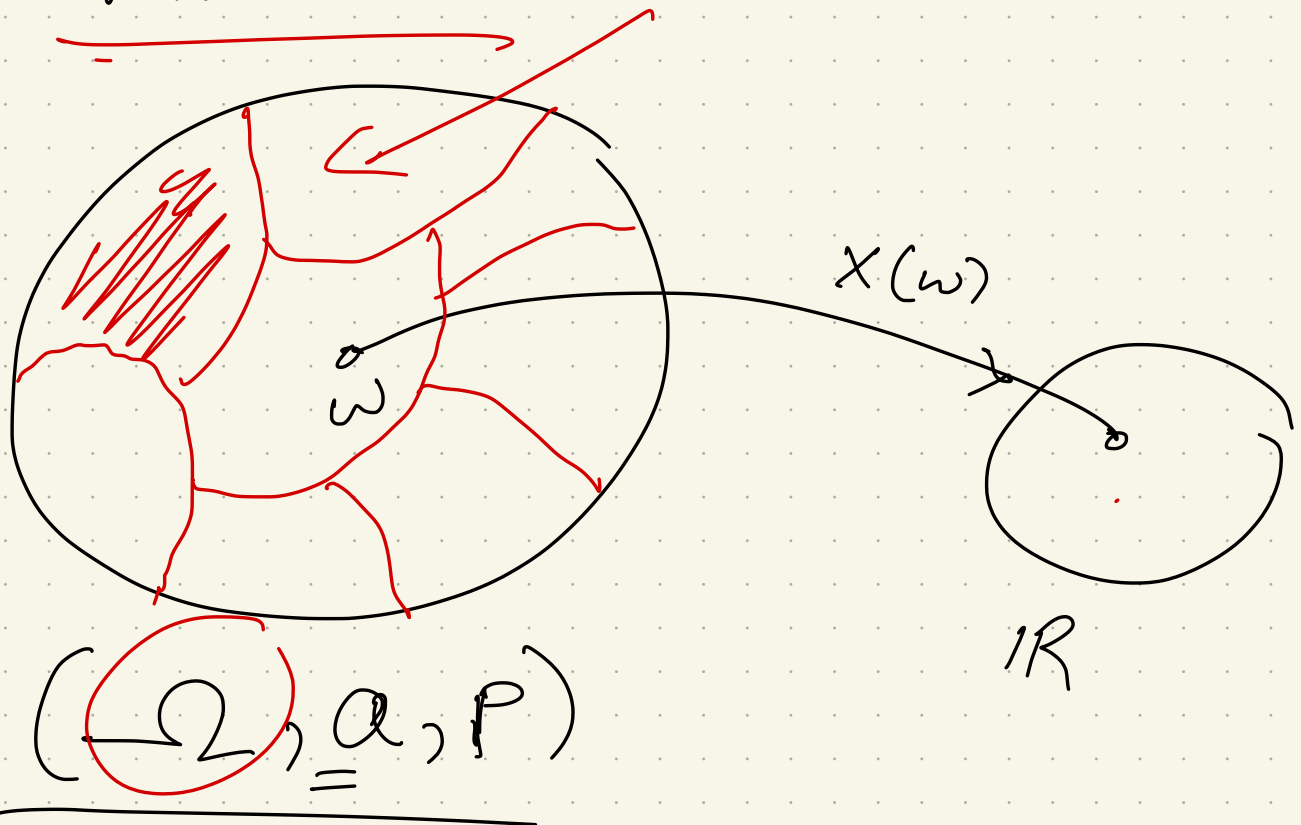
finite. That is essentially equivalent

to $E(|y|) < \infty$

Non-negative random variables
always have an expectation → could
be infinite.

But ^a general random variable is
only assigned an expectation if- its
absolute magnitude has ^{finite} expectation.

X : some non-negative random variable



consider a simple random variable
first. Call it S

$$S(\omega) = \sum_{j=1}^l x_j 1(\omega \in A_j)$$

Where A_1, A_2, \dots, A_l form
a partition of Ω

Let \widetilde{S} be a non-negative simple random variable.

$$\widetilde{S}(\omega) = \sum_j \widetilde{x}_j 1(\omega \in \widetilde{A}_j)$$

$$\widetilde{A}_1 \cup \dots \cup \widetilde{A}_\ell = \Omega$$

$$\widetilde{x}_j \geq 0$$

$$E[\widetilde{S}] \text{ is defined intuitively} \\ \approx \sum_{j=1}^{\ell} \widetilde{x}_j P(\widetilde{A}_j)$$

If $X \geq 0$, take a sequence
of non-negative simple random
variables $\tilde{S}_1 \leq \tilde{S}_2 \leq \tilde{S}_3 \leq \dots$
such that

for each $\omega \in \Omega$, $X(\omega) = \uparrow \lim_{j \rightarrow \infty} \tilde{S}_j(\omega)$

Define $E[X] = \uparrow \lim_{j \rightarrow \infty} E[\tilde{S}_j]$

\tilde{S} and \tilde{S}' are non-negative
simple random variables

and $\tilde{S} \leq \tilde{S}'$,

then $E\tilde{S} \leq E(\tilde{S}')$!

Prove -