

Midterm 1 : STA 5447

February 23rd 2006

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34 | 35

- Please write your name here.

MAHTAB MARKER

- Please provide detailed answers to all questions.

- Maximum number of points = 35.

①

Definitions and examples

(8 points)

8/8

(a) Let ν_1 and ν_2 be two measures on a σ -field.

- ② 1) When is ν_1 absolutely continuous wrt ν_2 ?
2) When is ν_1 singular wrt ν_2 ?

(b) Give an example of two measures satisfying a-1) and

① of two measures satisfying a-2).
(No proof required).

(c)

Define:

- 1) The product space of two measurable spaces. ①
2) The product measure. ①

- (d) Let F be a distribution function.
Define its inverse. (1)
- (e) Let $\{X_n\}_m$ and $\{Z_n\}_m$ be two sequences
of random variables. When do we (1)
say that they are Khinchin-equivalent?
- (f) Give an example of two sequences
that are Khinchin-equivalent.
(No proof required). (1)

- (I) (a) If ν_1 and ν_2 are 2 meas on a σ -field \mathcal{A} we say
- 1) ν_1 is abs continuous wrt ν_2 denoted by $\nu_1 \ll \nu_2$
 if $\nu_2(A) = 0 \Rightarrow \nu_1(A) = 0$ for any $A \in \mathcal{A}$
 - 2) ν_1 is singular wrt ν_2 denoted by $\nu_1 \perp \nu_2$
 if $\exists A \in \mathcal{A}$ st $\nu_1(A) = 0$ and $\nu_2(A^c) = 0$

- (b) If ν_2 is λ the lebesgue meas then
- let $X \sim \text{Normal}(\mu, \sigma^2)$ with induced meas P_X
 $Y \sim \exp(\gamma)$ with induced meas P_Y
 $\lambda_0(A) \equiv \lambda(A \cap [0,1])$ lebesgue meas restricted to
 the interv $[0,1]$
- $Z \sim \text{Pois}(e_g)$ with induced meas P_Z
 $W \sim \text{Bin}(n, p)$ with induced meas P_W
 $M \equiv$ counting meas on \mathbb{Z} (the set of integers $0, 1, 2, \dots$)

then	$P_X \ll \lambda$	$P_Z \perp \lambda$
	$P_Y \ll \lambda$	$P_W \perp \lambda$
	$\lambda_0 \ll \lambda$	$\mu \perp \lambda$

(c) 1). Product Space:

if (Ω, \mathcal{A}) and (Ω', \mathcal{A}') are 2 measurable spaces

let $\mathcal{F} = \left\{ \sum_{i=1}^m A_i \times A'_i : m \geq 1, A_i \in \mathcal{A}, A'_i \in \mathcal{A}' \right\}$

and $\mathcal{A} \times \mathcal{A}' = \sigma[\mathcal{F}]$

then $(\Omega \times \Omega', \mathcal{A} \times \mathcal{A}')$ is the product space of the two measurable spaces.

2) Product Measure

$(\Omega, \mathcal{A}, \mu)$ and $(\Omega', \mathcal{A}', \nu)$ are 2 measure spaces

$\mathcal{A} \times \mathcal{A}' = \sigma[\mathcal{F}]$

$\mathcal{F} = \left\{ \sum_{i=1}^m A_i \times A'_i : m \geq 1, A_i \in \mathcal{A}, A'_i \in \mathcal{A}' \right\}$

and $(\Omega \times \Omega', \mathcal{A} \times \mathcal{A}')$ is the product space

let $\Phi\left(\sum_{i=1}^m A_i \times A'_i\right) = \sum_{i=1}^m \mu(A_i) \times \nu(A'_i)$

then Φ is a well defined σ -finite measure on \mathcal{F}

and Φ extends uniquely to $\mathcal{A} \times \mathcal{A}'$ and it is called the product measure

(d) F is the distⁿ functⁿ

$$F^{-1}(t) = \inf\{y \mid F(y) \geq t\} \quad \text{for } t \in [0, 1]$$

is the quantile functⁿ

(e) $\{X_n\}$ and $\{Y_n\}$ are a seq of rv. We say they are k -equivalent if $\sum_{n=1}^{\infty} P(X_n \neq Y_n) < \infty$

(f) Let $Y_n = X_n I_{[|X_n| < n]}$ and $\{X_n\}$ is any seq of

iid random variables with $E|X_1| < \infty$

then $\{X_n\}$ and $\{Y_n\}$ are K -equivalent.

II

Statements and examples with proofs.

12 points

12/12

(a) State the Radon-Nikodym Theorem
for finite measures. (2)

(2) Let λ be the Lebesgue measure.
Give an example of a measure $\mu \ll \lambda$ and
 μ s.t. calculate $\frac{d\mu}{d\lambda}$. (2)

(b) Let $\xi \sim \text{Unif}(0, 1)$. Define $X = F^{-1}(\xi)$.
Show that X has distribution F , where
 F is a given distribution function.

(2)  Hint No need for the full proof
of step 1 of this result. Just state
the result you need to make
your (one line!) argument. \square

(c) Let X_1, \dots, X_n be i.i.d. random variables.

Under what additional ^{minimal} assumption
on $X_i, i=1, n$, can we conclude that

① $\sum_{m=1}^{\infty} P(|X_m| \geq m) < \infty$?

(Just state the assumption; no proof
required).

② (a) State the weak law of large numbers.

④ (e) Give the outline of the proof of
the WLLN. Only the statement
of the main steps is required.

(II) (a)

i) Radon - Nikodyn Theorem

μ and Φ are meas and signed meas, both σ -finite
on (Ω, \mathcal{A}) then we say

$\Phi << \mu \iff \exists$ a z_0 , meas, finite valued, unique a.e
wrt μ st

$$\Phi(A) = \int_A z_0 d\mu \quad \text{for any } A \in \mathcal{A}$$

$[z_0 = \frac{d\Phi}{d\mu}$ is called the R-N derivative of Φ wrt $\mu]$

2) λ is the lebesgue measure

let $X \cong N(\mu, \sigma^2)$ with induced meas P_{μ, σ^2}

then $P_{\mu, \sigma^2} << \lambda$ and

$$P_{\mu, \sigma^2}(A) = \int_A \frac{1}{\sqrt{2\pi}} \frac{1}{\sigma} \exp \left\{ -\frac{1}{2\sigma^2} (x-\mu)^2 \right\} d\lambda(x)$$

here $\frac{dP_{\mu, \sigma^2}}{d\lambda}(x) = \frac{1}{\sqrt{2\pi}} \cdot \frac{1}{\sigma} \exp \left\{ -\frac{1}{2\sigma^2} (x-\mu)^2 \right\}$

$$(b) \quad \epsilon_g \sim \text{Unif}(0,1)$$

$$X \equiv F^{-1}(\epsilon_g)$$

$$\text{Proof: } \{ \omega \mid X(\omega) \leq x \} = \{ \omega \mid \epsilon_g(\omega) \leq F(x) \} \quad (\text{we can show})$$

$$\begin{aligned} \text{Now } F_X(x) &= P(X \leq x) = P(\{\omega \mid X(\omega) \leq x\}) \\ &= P(\{\omega \mid \epsilon_g(\omega) \leq F(x)\}) \\ &= P(\epsilon_g \leq F(x)) \end{aligned}$$

$$= F(x) \quad [\because \epsilon_g \sim \text{Unif}(0,1)]$$

$\therefore X$ has df F

$$\text{To show } \{ \omega \mid X(\omega) \leq x \} = \{ \omega \mid \epsilon_g(\omega) \leq F(x) \}$$

$$\begin{aligned} \text{let } \omega_0 \in \Omega \text{ st } \epsilon_g(\omega_0) \leq F(x) &\Rightarrow F^{-1}(\epsilon_g(\omega_0)) \leq F^{-1}(F(x)) \\ &\leq x \quad \{ F^{-1}F(x) \leq x \} \\ &\Rightarrow X(\omega_0) \leq x \end{aligned}$$

$$\begin{aligned} \text{let } \omega_0 \in \Omega \text{ st } X(\omega_0) \leq x &\Rightarrow F^{-1}(\epsilon_g(\omega_0)) \leq x \\ &\Rightarrow \inf \{ y \mid F(y) \geq \epsilon_g(\omega_0) \} \leq x \end{aligned}$$

$$\text{let } y_0 = \inf \{ y \mid F(y) \geq \epsilon_g(\omega_0) \} \text{ then } y_0 \leq x$$

$$\forall \varepsilon > 0 \exists y_\varepsilon \in \{ y \mid F(y) \geq \epsilon_g(\omega_0) \} \text{ st } y_\varepsilon - \varepsilon \leq y_0$$

$$\therefore \text{we have } \begin{cases} y_0 + \varepsilon \geq y_\varepsilon \\ x - y_0 \geq 0 \end{cases} \Rightarrow x + \varepsilon \geq y_\varepsilon$$

$$\text{since } F \text{ is df it is } \Rightarrow F(x + \varepsilon) \geq F(y_\varepsilon)$$

$$F(x+\varepsilon) \geq F(y_\varepsilon) \geq g(w_0)$$

$$\Rightarrow F(x+\varepsilon) \geq g(w_0)$$

$$\Rightarrow F(x) \geq g(w_0)$$

{ by continuity, taking $\varepsilon \rightarrow 0$

\therefore we have shown " \subseteq " and " \supseteq "

(c) $X_1, X_2, \dots, X_n, \dots$ are iid r.v.

If $E|X| < \infty$ then $\sum_{n=1}^{\infty} P(|X_n| \geq n) < \infty$

Proof uses the fact that for any r.v. X

$$\sum_{n=1}^{\infty} P(|X| \geq n) \leq E|X| \leq \sum_{n=1}^{\infty} P(|X| \geq n) + P(|X| \geq n)$$

$$\text{So if } E|X| < \infty \Rightarrow \sum_{n=1}^{\infty} P(|X| \geq n) < \infty$$

(d) The Weak Law of Large Numbers:

If $X_1, X_2, \dots, X_n, \dots$ are iid r.v. with mean μ and

$$E|X_1| < \infty \text{ then}$$

that is $X_n \xrightarrow[n \rightarrow \infty]{P} \mu$

$$\bar{X}_n \xrightarrow[n \rightarrow \infty]{P} \mu$$

$$\text{where } \bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$$

II

(e) Proof of WLLN

(i) let $Y_{nk} = X_k I_{[|X_k| < n]}$ and $\bar{Y}_n = \frac{1}{n} \sum_{k=1}^n Y_{nk}$

(ii) $\mu_n = E(Y_{nk})$

(iii) show $\{X_n\}$ and $\{Y_n\}$ are k-equivalent

\Rightarrow If $\bar{Y}_n \rightarrow$ in P to some Y then $\bar{X}_n \xrightarrow{P} \text{to the same } Y$

(iv) show $\bar{Y}_n \xrightarrow{\mathbb{R}} \mu_n \xrightarrow{P} 0$ as $n \rightarrow \infty$

(v) show $\mu_n \rightarrow \mu$ as $n \rightarrow \infty$

$\Rightarrow \bar{Y}_n \xrightarrow{P} \mu$ as $n \rightarrow \infty$

i. $\bar{X}_n \xrightarrow{P} \mu$ (by step (iii))

Exercise 1

3 points

3/3

Let X_1, \dots, X_m be i.i.d random variables such that

$$\sum_{i=1}^m e^{-X_i} \xrightarrow{\text{a.s.}} U, \text{ for some given r.v. } U.$$

Find the almost sure limit of

$$\sum_{i=1}^m e^{(i-X_i-n)}$$

Exercise 2

5 points

5/5

Let $X \geq 0$ be a r.v. with df F .

$$\text{Show that } E X = \int_0^\infty (1 - F(x)) dx.$$

Give full explanations at each step
and check the conditions of every
result you apply in order to receive
full credit.

Exercise 1

$x_1, x_2, \dots, x_n, \dots$ are iid random variables st

$$\sum_{i=1}^n e^{-x_i} \xrightarrow{a.s} u \text{ (for some given r.v. } u)$$

Now consider

$$\sum_{i=1}^n e^{i-x_i-n} = \sum_{i=1}^n \frac{e^i \cdot e^{-x_i}}{e^n}$$

$$= \sum_{k=1}^n \frac{b_k z_k}{b_n}$$

$$\text{with } b_k = e^i \quad z_k = e^{-x_i}$$



$$\text{Notice } \lim_{k \rightarrow \infty} b_k = e^\infty = \infty$$

\therefore we have a seq $\{b_k\}$ st $b_k \uparrow \infty$

we have $\sum_{k=1}^n z_k \xrightarrow{a.s} u$ (for some u)

$\therefore \sum_{k=1}^n \frac{b_k z_k}{b_n} \xrightarrow{a.s} 0$ (by Kronecker's lemma)

Exercise 2 $X \geq 0$ is a r.v with df F . [say X is def on (Ω, \mathcal{A}, P)]

$$E(X) = \int_{\Omega} X(\omega) dP(\omega)$$

$$= \int_{\Omega} \left[\int_0^{X(\omega)} d\lambda(t) \right] dP(\omega) \quad \left\{ \lambda \text{ is Lebesgue meas} \right.$$

$$= \int_{\Omega} \int_0^{\infty} I_{[0 < t < X(\omega)]} d\lambda(t) dP(\omega)$$

$$= \int_0^{\infty} \int_{\Omega} I_{[0 < t < X(\omega)]} dP(\omega) d\lambda(t) \quad \begin{cases} \text{by Tonelli since} \\ I_{[0 < t < X(\omega)]} \geq 0 \text{ always} \end{cases}$$

$$= \int_0^{\infty} P(X(\omega) > t) d\lambda(t)$$

$$= \int_0^{\infty} (1 - F(t)) dt \quad \left\{ \text{by definition of } F(t) \right.$$

Note: Here if we use $I_{[0 < t \leq X(\omega)]}$ it is also

ok since F is rt continuous and $E(0) = 0$

Exercise 3

7 points

1/7

(5)

a) Let X_1, \dots, X_n be iid with common cdf $F(x) = (1 - e^{-x})$.

2/5

Show that
Define $Y_n = \max_{1 \leq i \leq n} X_i$.

$$P\left(\lim_{n \rightarrow \infty} \frac{Y_n}{\log n} \leq 1\right) = 0$$

$$\lim_{n \rightarrow \infty} \frac{Y_n}{\log n} \geq 1 \quad \text{a.s.}$$

$$P\left(\frac{Y_n}{\log n} \leq 1 \text{ i.o.}\right) = 0$$

↓ State the results you use.
You may need to use the known inequality
 $1-x \leq e^{-x}$. ↑

$$\sum P\left(\frac{Y_n}{\log n} \leq 1\right) < \infty$$

b) Let $X_n \sim N(0, n^{\frac{1}{4}})$. Show that

(2)

$$\frac{X_n}{n} \xrightarrow{\text{a.s.}} 0.$$

2/2

↓ State the results you are using. ↑

$$1 - e^{-x} \leq x$$

(13)

Exercise 3

$X_1, X_2, \dots, X_n, \dots$ are iid with $F(x) = (1 - e^{-x})$

$$Y_n \equiv \max_{1 \leq i \leq n} X_i$$

$$\text{Consider } P\left(\frac{Y_n}{\log n} \leq 1\right)$$

$$= P(Y_n \leq \log n)$$

$$= P\left(\max_{1 \leq i \leq n} X_i \leq \log n\right)$$

$$\leq \frac{\text{Var}(X_n)}{\log n}$$

Kolmogorov's
maximal inequality

If we show $\sum_{n=1}^{\infty} \frac{\text{Var}(X_n)}{\log n} < \infty$ then

This is $\Rightarrow \sum_{n=1}^{\infty} P\left(\frac{Y_n}{\log n} \leq 1\right) < \infty$
 indeed what's needed --

$$\Rightarrow P\left(\frac{Y_n}{\log n} \leq 1 - \varepsilon_{10}\right) = 0 \quad \left\{ \text{Borel-Cantelli 1} \right.$$

$$\Rightarrow P\left(\lim \frac{Y_n}{\log n} \leq 1 - \varepsilon\right) = 0$$

$$\Rightarrow \lim \frac{Y_n}{\log n} \geq 1 \quad \text{a.s}$$

To show $\sum_{n=1}^{\infty} \frac{\text{Var}(X_n)}{(\log n)} < \infty$

Consider $\sum_{n=1}^{\infty} \frac{\text{Var}(X_n)}{\log n} \leq \sum_{n=1}^{\infty} \frac{E(X_n^2)}{(\log n)} = \sum_{n=1}^{\infty} \frac{2}{\log n} < \infty$

Now $E(X_n^2) = \int_0^{\infty} 2t(1-F(t))dt$

$$= \int_0^{\infty} 2t e^{-t} dt$$

$$= \left\{ 2(-e^{-t})t \Big|_0^{\infty} + 2 \int_0^{\infty} e^{-t} dt \right\}$$

$$= 2e^0 + 2(-e^{-t}) \Big|_0^{\infty}$$

$$= 2e^0$$

$$= 2$$

No!

Exercise 3

$$(b) \quad X_n \sim N(0, n^{1/4})$$

To show $\frac{X_n}{n} \xrightarrow{\text{a.s.}} 0$

To show $P\left(\left|\frac{X_n}{n}\right| > \varepsilon \text{ i.o.}\right) = 0$

$$\text{Consider } P\left(\left|\frac{X_n}{n}\right| > \varepsilon\right) = P(|X_n| > n\varepsilon)$$

$$\leq \frac{\text{Var}(X_n)}{n^2 \varepsilon^2}$$

{ by Chebyshev's
ineq.

$$= \frac{n^{1/4}}{n^2 \varepsilon^2}$$

$$= \frac{1}{n^{(2-1/4)} \varepsilon^2} \quad \checkmark$$

$$\xrightarrow[n \rightarrow \infty]{} 0$$

$$\Rightarrow \sum_{n=1}^{\infty} P\left(\left|\frac{X_n}{n}\right| > \varepsilon\right) < \infty \quad \{ \text{since the tail} \rightarrow 0$$

$$\Rightarrow P\left(\left|\frac{X_n}{n}\right| > \varepsilon \text{ i.o.}\right) = 0 \quad \{ \text{Borel Cantelli 1}$$

$$\Rightarrow \frac{X_n}{n} \xrightarrow{\text{a.s.}} 0 \quad \{ \text{by equivalent cond'n for almost sure convergence.}$$

Exercise 3

(Alternate approach)

NOT COMPLETED

To show $P\left(\lim \frac{Y_n}{\log n} \leq 1\right) = 0$

$$\Leftrightarrow P\left(\frac{Y_n}{\log n} \leq 1 \text{ i.o.}\right) = 0$$

\therefore We can show $\sum_{n=1}^{\infty} P\left(\frac{Y_n}{\log n} \leq 1\right) < \infty$

$$P\left(\frac{Y_n}{\log n} \leq 1\right) = P(Y_n \leq \log n)$$

$$= P\left(\max_{1 \leq i \leq n} X_i^o \leq \log n\right)$$

$$= \prod_{i=1}^n P(X_i^o \leq \log n)$$

$$= \prod_{i=1}^n (1 - e^{-\log n})$$

$$= \left(1 - n^{-1}\right)^n$$

$$\leq (e^{-1})^n$$

$$= e^{-1}$$

Ex 3. MIDTERM

Show $\overline{\lim}_{\log n} \frac{y_n}{\log n} \geq 1$ a.s

To show $P\left(\left[\left(\frac{y_n}{\log n} \geq 1-\varepsilon\right)_{i_0}\right]\right) = 1$

OR $P\left(\frac{y_n}{\log n} \leq 1-\varepsilon_{i_0}\right) = 0$

To show $\sum_{n=1}^{\infty} P\left(\frac{y_n}{\log n} \leq 1-\varepsilon\right) < \infty$

$$P(y_n \leq (1-\varepsilon)\log n) = P(\max x_n \leq (1-\varepsilon)\log n)$$

$$= \prod_{i=1}^n P(x_i \leq (1-\varepsilon)\log n)$$

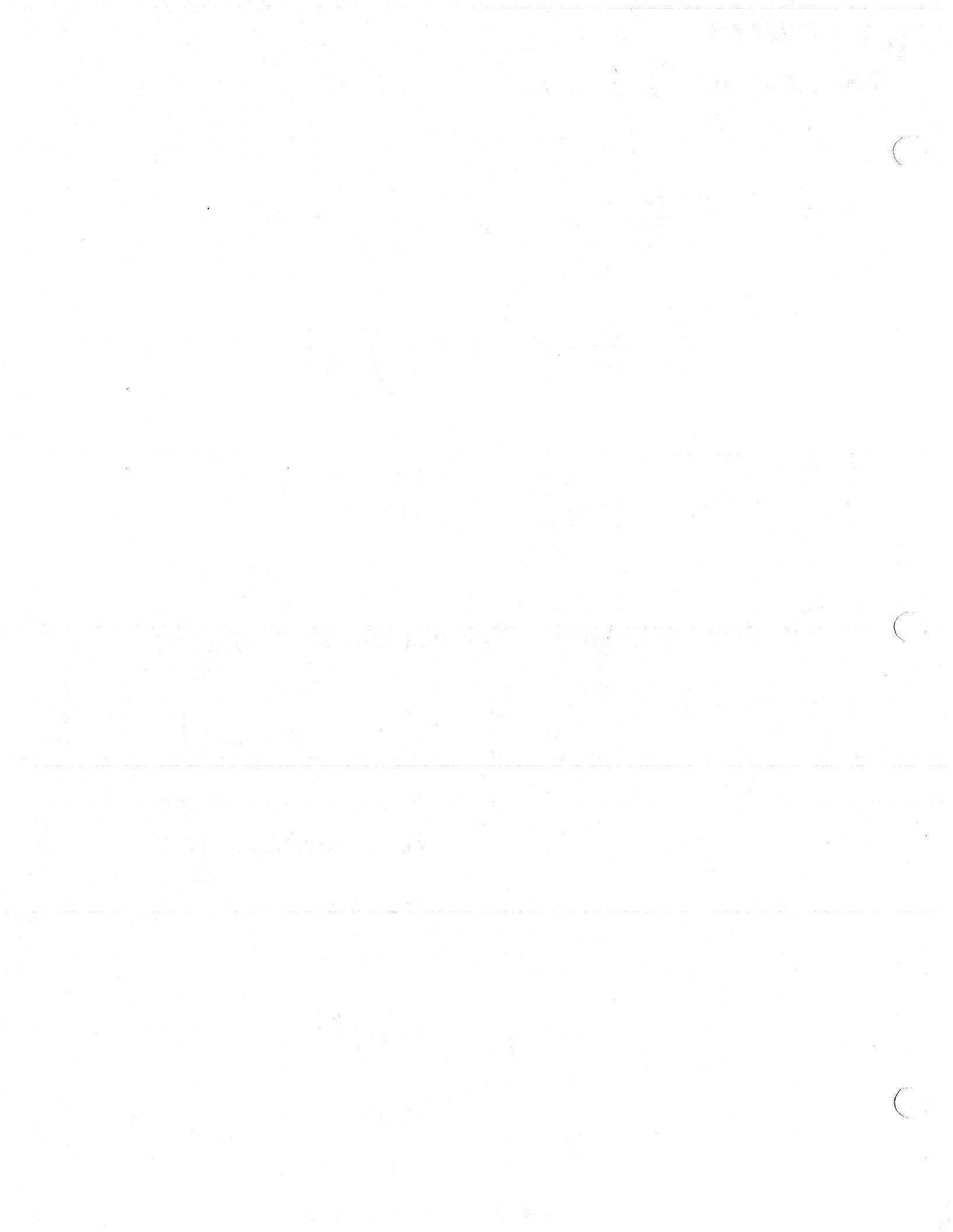
$$= \left[P(x_n \leq (1-\varepsilon)\log n)\right]^n$$

$$= \left[1 - e^{-\log^{(1-\varepsilon)} n}\right]^n$$

$$= \left[1 - n^{-(1-\varepsilon)}\right]^n$$

$$\leq \left[e^{-(n^{\varepsilon-1})}\right]^n = \left(e^{-n^{\varepsilon} n^{-1}}\right)^n = e^{-n^\varepsilon}$$

$\rightarrow 0$ as $n \rightarrow \infty$



1D TERM

$$\left| \sum_{k=1}^n E \left(Y_k I_{[|Y_k| \leq \sqrt{n}]} \right) \right|^4$$

$$\leq \sum_{k=1}^n \left(E |Y_k| I_{[|Y_k| \leq \sqrt{n}]} \right)^4$$

$$\leq \sum_{k=1}^n \left(\frac{1}{\sqrt{n}} \right)^4$$

$$= \frac{n}{n^2}$$

$$= \frac{1}{n} \longrightarrow 0$$



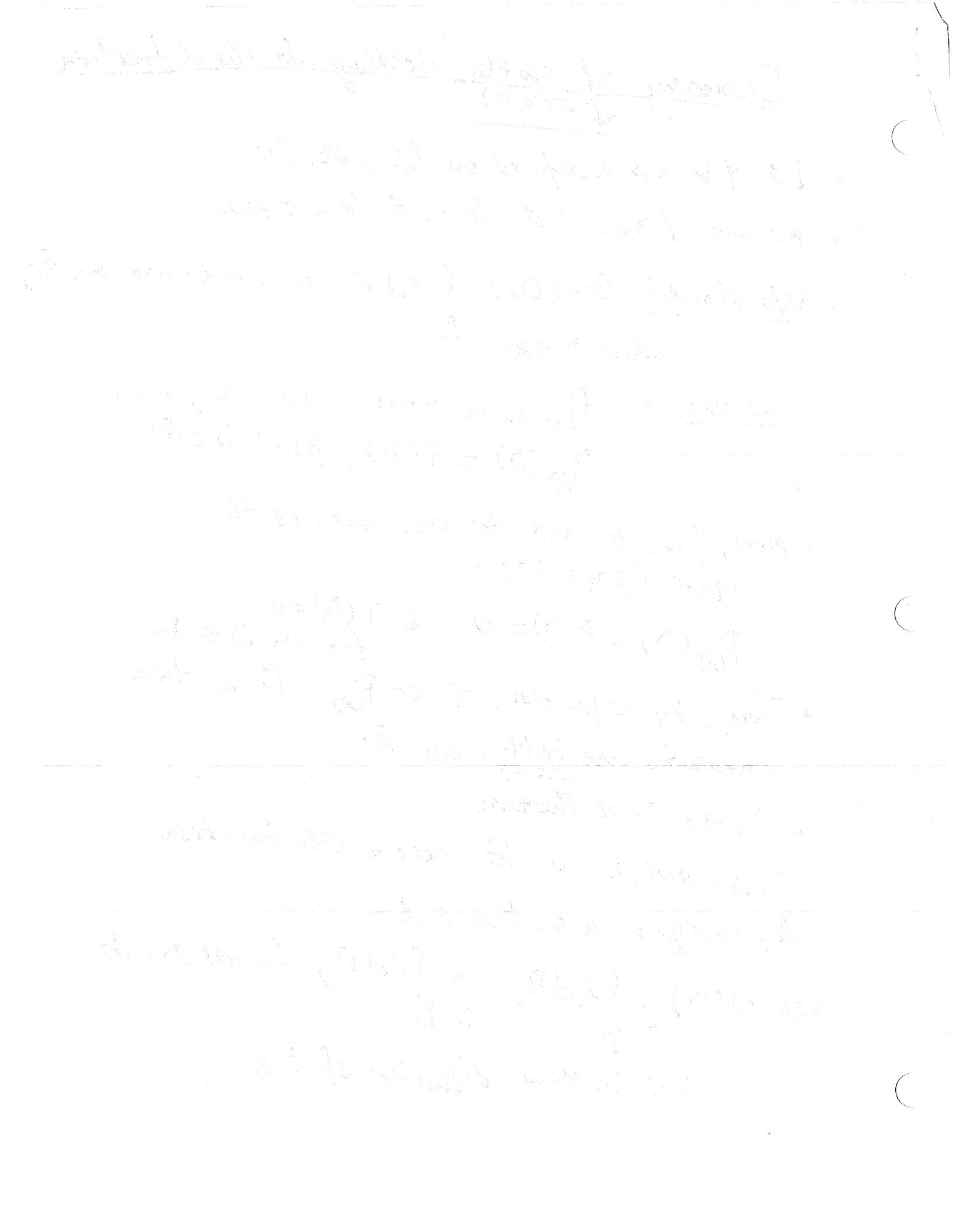
Summary of results yielding to the definition
of $E(Y|\mathcal{D})$.

- Let Y be a s.v. defined on (Ω, \mathcal{A}, P) .
- Assume $Y \geq 0$. Let $\mathcal{D} \subset \mathcal{A}$ be a σ -field.
- We showed : ① $\nu(D) = \int_Y dP$ is a measure on \mathcal{D} , where $D \in \mathcal{D}$.
- We showed : $P_{|\mathcal{D}}$ is a measure on \mathcal{D} , where $P_{|\mathcal{D}}(D) = P(D)$, for all $D \in \mathcal{D}$.
- Now, from ① and the obs. cont. of the integral (page 42) :

$$P_{|\mathcal{D}}(D) = P(D) = 0 \Rightarrow \nu(D) = 0, \text{ for all } D \in \mathcal{D}.$$
- Thus, by definition, $\nu \ll P_{|\mathcal{D}}$. These two measures are both on \mathcal{D} .
- By the R-N Theorem :
There exists a \mathcal{D} -measurable function h , unique a.s. $P_{|\mathcal{D}}$ s.t. :

$$\nu(D) = \int_D h dP_{|\mathcal{D}} = \int_D h dP, \text{ for all } D \in \mathcal{D}.$$

R-N Theoreme definition of $P_{|\mathcal{D}}$



- From ① and ② :

$\exists h$, \mathcal{D} -measurable and integrable a.s. $P_{|\mathcal{D}}$ s.t.

$$③ \int_Y dP = \int_D h dP, \quad \forall D \in \mathcal{D}.$$

- Result: If h is \mathcal{D} -measurable and integrable a.s. $P_{|\mathcal{D}}$
then h is integrable a.s. P .

Combining ③ and Result gives:

Combining ③ and Result gives:
 $\exists h$, \mathcal{D} -measurable, an integrable a.s. P s.t.

$$\int_Y dP = \int_D h dP, \quad \forall D \in \mathcal{D}.$$

- This function h is denoted by $E(Y|\mathcal{D})$
and called the conditional expectation of
 Y with respect to \mathcal{D} , and so:

$$\int_Y dP = \int_D E(Y|\mathcal{D}) dP, \quad \forall D \in \mathcal{D}.$$

