

By definition, a function  $f: \Omega \rightarrow [-\infty, \infty]$  is a random variable ("measurable") if  $f^{-1}(B) \in \mathcal{F}$  for every Borel-set  $B \subseteq [-\infty, \infty]$ .  
 Conversely, every measurable function satisfies the "level set condition":  
 Let  $\Omega = \{B \subseteq [-\infty, \infty] : f^{-1}(B) \in \mathcal{F}\}$ . Then  
 (i)  $[-\infty, \infty] \in \mathcal{G}$   
 (ii) If  $B \in \mathcal{G}$  then  $f^{-1}([-\infty, \infty] \setminus B) = f^{-1}([-\infty, \infty]) \setminus f^{-1}(B)$  is closed under complemen-  
 tion.  
 (iii) If  $B_1, B_2 \in \mathcal{G}$  then  $f^{-1}(B_1 \cap B_2) = f^{-1}(B_1) \cap f^{-1}(B_2)$  is closed under finite intersections.  
 (iv) If  $(B_n) \subset \mathcal{G}$  then  $f^{-1}(\bigcup B_n) = \bigcup f^{-1}(B_n) \in \mathcal{F}$ .  
 So  $\mathcal{G}$  is closed under countable unions.  
 So  $\mathcal{G}$  is a  $\sigma$ -field.

From proposition  
 (i)  $[-\infty, \infty] \in \mathcal{G}$   
 (ii) If  $B \in \mathcal{G}$  then  $f^{-1}([-\infty, \infty] \setminus B) = f^{-1}([-\infty, \infty]) \setminus f^{-1}(B) \in \mathcal{F}$ . Then  
 $f^{-1}(B) \in \mathcal{F}$ . So  $f^{-1}(B)$  is closed under complemen-  
 tion.  
 (iii) If  $B_1, B_2 \in \mathcal{G}$  then  $f^{-1}(B_1 \cap B_2) = f^{-1}(B_1) \cap f^{-1}(B_2)$  is closed under finite intersections.  
 (iv) If  $(B_n) \subset \mathcal{G}$  then  $f^{-1}(\bigcup B_n) = \bigcup f^{-1}(B_n) \in \mathcal{F}$ .  
 So  $\mathcal{G}$  is a  $\sigma$ -field.

By definition, a function  $f: \Omega \rightarrow [-\infty, \infty]$  is a random variable ("measurable") if  $f^{-1}(B) \in \mathcal{F}$  for every Borel-set  $B \subseteq [-\infty, \infty]$ .  
 A short argument:  
 Let  $f: \Omega \rightarrow [-\infty, \infty]$  be a random variable.  
 Then  $f^{-1}(\mathcal{G}) \subseteq \mathcal{F}$ .  
 Now  $\mathcal{G}$  is a  $\sigma$ -field.  
 So  $f^{-1}(\mathcal{G})$  is a  $\sigma$ -field.  
 So  $f^{-1}(\mathcal{G}) = \mathcal{G}$ .

Lemma

A/R

Let  $f: \mathbb{R} \rightarrow [-\infty, \infty]$  be measurable and  $g: \mathbb{R} \rightarrow \mathbb{R}$  a

Borel measurable function. Let  $\mathcal{B}$  denote the Borel  $\sigma$ -field on  $\mathbb{R}$ . The  $g \circ f$  is measurable too.

But  $f^{-1}(g^{-1}(H)) = ((g \circ f)^{-1}(H))$ .

□

Let  $h \in \mathcal{B}$  then  $g^{-1}(h) \in \mathcal{B}$  and so  $f^{-1}(g^{-1}(h)) \in \mathcal{B}$

Lemma

If  $f$  is measurable and  $f^+ = \max\{f, 0\}$ ,  $f^- = \max\{-f, 0\}$

while  $|f| = f^+ + f^-$ . Then  $f^+$ ,  $f^-$ ,  $|f|$  are all measurable,

Set  $g_+(x) = \max\{x, 0\}$ ,  $g_-(x) = \max\{x, 0\}$ ,  
 $g(x) = |x|$ . Each of those are  $\mathcal{B}$  fm. So, by the previous

lemma,  $g_+(f) = f^+$ ,  $g_-(f) = f^-$  and  $g(|f|) = |f|$  are measurable.

Suppose that  $f: \mathcal{A} \rightarrow [-\infty, \infty]$  is the pointwise limit of simple random variables,  $\Delta_n$ . So  $\Delta_n \leftarrow f_{n+1}$ ,

Then  $f$  is (a random variable) measurable.

Let me N, then, as  $\Delta_n(\omega) \leftarrow f(\omega)$ , should we  $\{f \leq x\}$

we have  $\{f \leq x\} = \bigcup_{n=1}^{\infty} \bigcap_{m=1}^{\infty} \{f_n \leq x + \frac{1}{m}\}$  and therefore  $f(\omega) = \lim_{n \rightarrow \infty} \Delta_n(\omega) \leq x + \frac{1}{m}$ .

then for each  $n \in \mathbb{N}$  there  $\{f_n \leq x + \frac{1}{m}\}$  such that

$\bigcup_{n=1}^{\infty} \bigcap_{m=1}^{\infty} \{f_n \leq x + \frac{1}{m}\} \subseteq \{f \leq x\}$ . Thus

So  $f$  is measurable.  $\square$  Hence Borel measurable.

$$E(f) = \int f dP \leq \int f_+ dP - \int f_- dP$$

Definition Let  $f$  be a random variable. We define  $E(f)$ , the expectation of  $f$  with respect to  $P$ , to be

PF Previous lemma.

$$\min\{f_+, f_-\} \leq f \leq \max\{f_+, f_-\} = \frac{f_+ + f_-}{2} + \frac{|f_+ - f_-|}{2}$$

$$\max\{f_+, f_-\} \leq f \leq \frac{f_+ + f_-}{2} + \frac{|f_+ - f_-|}{2}$$

Let  $F, F_+$  be random variables, then so are

Lemma

E.f.

$$\{f = \frac{f_+ - f_-}{2}\} = P\{f_+ > f_-\} \in \mathcal{F}_0 \{f_+ < f_-\} = \{f_+ < f\} \cap \{f_+ > f_-\}$$

$$\{f < \frac{f_+}{2}\} = \{f < f_+\} \in \mathcal{F}_0 \{f < f_+\} \in \mathcal{F}_0 \text{ and } \{f < \frac{f_-}{2}\} = \{f < f_-\} \in \mathcal{F}_0 \{f < f_-\} \in \mathcal{F}_0$$

$$\{hf < 0\} = \{f < -\frac{1}{h}\} \in \mathcal{F}. \text{ If } h < 0 \text{ note that}$$

If  $h = 0$ ,  $hf$  is simple random variable. If  $h > 0$  then

random variable. So  $f+g$  is a random variable by the previous lemma. — which is again a consequence of simple random variable formed by the corresponding linear combination of simple sequences formed by the linear combination of simple random variables. If  $h = 0$ ,  $hf$  is simple random variable by the limit of the

increasing) sequence of simple random variables. Any linear combination of these random variables is the limit of an increasing sequence of simple random variables. Each of these is the limit of a linear combination of simple random variables and we know that each of these is the limit of an

$$Pf + g = f_+ - f_- + g_+ - g_-. \text{ Each of } f_+, f_-, g_+, g_- \text{ are random}$$

variables. Also if  $h \in \mathbb{R}$ , then  $hf$  is a random variable.

Let  $f, g$  be random variables. Then  $f+g$  is a random

Lemma

$$\int_a^x f'_t dt + \int_a^x g'_t dt = f(x) - f(a) + g(x) - g(a)$$

$$\int_a^x f'_t dt - \int_a^x g'_t dt = f(x) - g(x)$$

$$\int_a^x f'_t dt - \int_a^x g'_t dt - \int_a^x f'_t dt + \int_a^x g'_t dt = 0$$

and  $\int_a^x (f'_t + g'_t) dt = \int_a^x (f_t + g_t) dF$  using the definition and the lemma,  
 write  $f = f'_+ - f'_-$  and  $g = g'_+ - g'_-$  then  $f + g = f'_+ + g'_+$

The integral of a random variable with respect to  $F$ , well defined. The integral is a linear function.

Property

$$\int_a^x u'_t dt - \int_a^x v'_t dt = \int_a^x (u'_t - v'_t) dt$$

$$\int_a^x u'_t dt + \int_a^x v'_t dt = \int_a^x (u'_t + v'_t) dt = \int_a^x (u+v)'_t dt = \int_a^x (u+v)_t dF$$

Similar to the Monotone Convergence Theorem (for positive random variables),

$$\int_a^x u'_t dt - \int_a^x v'_t dt = \int_a^x (u-v)'_t dt = \int_a^x (u-v)_t dF$$

Suppose that  $f: \Omega \rightarrow [-\infty, \infty]$  is a random variable and also,  $f = u-v$ , where  $u \geq 0 \leq v$  are two random variables

Lemma  
 So long as at least one of the right hand integrals is finite.

$$\int f_n dP = \sup_{\Omega} \int_{\Omega} f_n dP$$

So  $\inf_{\Omega} \int_{\Omega} g_n dP = 0$ . Applying this to  $(f - f_n)$  we get

$$\int g_n dP = \inf_{\Omega} \int_{\Omega} g_n dP - \int_{\Omega} f_n dP$$

Thus  $\sup_{\Omega} \int_{\Omega} (g_n - f_n) dP = \int g_n dP$ , that is,  
 the monotone convergence theorem; since  $\sup_{\Omega} (g_n - f_n) = g_n - f$   
 Thus so are  $\int g_n dP$ ,  $n \geq 1$ . By our original version of  
 the monotone convergence theorem, consider r.v.'s. Suppose also that  $\int g_n dP < \infty$   
 which are non-negative and decreasing and converging  
 pointwise to 0. Then the sequence  $(g_n - f_n)$  is non-neg-  
 ative, increasing, converges r.v.'s. So  $f_n$  is a r.v.  
 Each  $f_n$  satisfies the level set condition,  $\{f_n \leq x\} \in \mathcal{E}_n$ , A  
 $\overline{\mathcal{E}}$

Thus  $f$  is a r.v. and  $\sup_{\Omega} \int_{\Omega} f_n dP = \int f dP$

(i)  $\int f_n dP$  exists for each  $n \in \mathbb{N}$ , and is finite.

(ii)  $f_n(\omega) \xrightarrow{n \rightarrow \infty} f(\omega)$  a.s.

(iii)  $f_1 \leq f_2 \leq \dots \leq f$

Let  $(f_n)$  be a sequence of r.v.'s such that  $f_n \downarrow \infty \leftarrow [f_n, \infty]$

The Monotone Convergence Theorem (for 'general' r.v.'s)

If  $f: \Omega \rightarrow [-\infty, \infty]$  is a random variable and  $F(\omega) = P(E|\omega)$ , then we say "almost surely" if  $Ef \geq 0$  almost everywhere, or, (in probabilistic language),  $Ef \geq 0$  almost everywhere, or, if  $f(\omega) \geq 0$  for every  $\omega \in \Omega$ . This kind of  $f$  is a function of  $\omega$  which is non-negative. If however  $f(\omega) \leq 0$  for some  $\omega \in \Omega$ , where  $f(\omega)$  is a function of  $\omega$  which is non-negative, then we say " $f \leq 0$  almost surely". If  $Ef \geq 0$  then we say " $f \geq 0$  almost surely" if there is  $N \in \mathcal{N}$  such that  $Ef \geq 0$  on  $E \setminus N$ . This kind of  $f$  is a function of  $\omega$  which is non-negative and  $Ef = 0$  and  $F(\omega) = 0$  for every  $\omega \in E \setminus N$ . A property  $P$  is said to hold on  $E$  if almost-surely  $f = g$  for every  $f, g$  be random variables. We say  $f = g$  almost surely on  $E$  iff  $E|f - g|^p = 0$  almost surely on  $E$ . In this case and  $F(\omega) = g(\omega)$  almost surely. One can also upon the probability measure  $P$ . One can also write  $f \sim g$ . Of course this idea depends upon the equivalence relation  $\sim$  which has zero integral because  $(f-g)P \in L^1$  in  $\mathcal{B}(\mathbb{R})$ , and thus has zero integral.

All of this emphasizes the fact that acts of zero probability measures are negligible in integration theory. Now you might think that a subset of a negligible set should also be negligible. However, there are examples of sets which are subsets of a set of zero measure but are not themselves measurable! This is because the  $\sigma$ -field that the (probability) measure is defined on is not as large as it could be. So, we could extend our  $\mathcal{E}$  so that  $P(A) = 0$  for every  $A \in \mathcal{N}$ , where  $\mathcal{N} \neq \emptyset$  and  $P(N) = 0$ . But is  $P$  still a measure on a  $\sigma$ -field? This is because the  $\sigma$ -field that the (probability) measure is defined on is not as large as it could be. So, we could extend our  $\mathcal{E}$  so that  $E$  be the collection of all  $E \subseteq \Omega$  for which there are sets  $H, J \in \mathcal{F}$  with  $H \subseteq E \subseteq J$  and  $P(J \setminus H) = 0$ . Then  $f$  is a  $\sigma$ -algebra and  $P$  is a complete probability space. Let  $(\Omega, \mathcal{F}, P)$  be a probability space. Let  $E$  be the collection of all  $E \subseteq \Omega$  for which there are sets  $H, J \in \mathcal{F}$  with  $H \subseteq E \subseteq J$  and  $P(J \setminus H) = 0$ . Then  $f$  is a  $\sigma$ -algebra and  $P$  is a complete probability space on  $\mathcal{F}$ . So  $(\Omega, \mathcal{F}, P)$  is a

Theorem

Therefore follows the following theorem.

Well, this is one possibility.

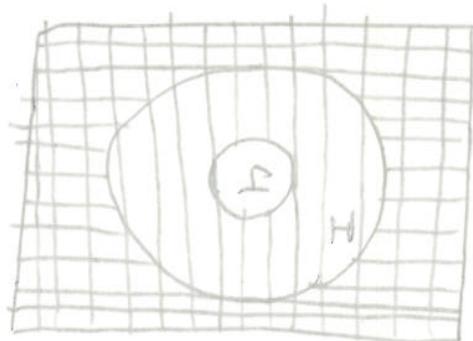
and  $\mathbb{P}(E \cap H) = 0$ , and also

So  $E \cap H = \emptyset$ . Suppose now that  $E \in \mathcal{F}$ .

$$0 = P(H \cap E) = P(H)P(E) > P(H)P(E)$$

$$\left. \begin{aligned} P(H \cap E) &= P(H) \\ P(H \cap E) &= P(H)P(E) \end{aligned} \right\} \text{because } P(H) > 0$$

Therefore, also  $P(H \cap E) < P(H)$ .  
Let  $T = \mathbb{P}(E)$ ,  $H = \mathbb{P}(H)$ , then  
 $T \in \mathcal{F}$  and  $H \in \mathcal{F}$ . Then  $E \cap H$  with  $P(H \cap E)$



$$T \cap H = P(H \cap T)$$

because  $H \cap T$  can be chosen that way and

$$P(T \cap H) = P((T \cap H) \setminus (T \cap E)) = P(H \cap T) = 0$$

so  $P(H \cap T) \leq P(E \cap T)$  and  $P(H \cap T) = 0$  in fact.

(iii) If  $E \in \mathcal{F}$  three and  $H \cap T$  in  $\mathcal{F}$  with  $P(H \cap T) = 0$

So  $P(H \cap T) = 0$

and that  $P(E)$  remains unchanged.

(i) If  $E \in \mathcal{F}$  then take  $H = E = T$  and see that  $E \in \mathcal{F}$

(\*) There are the same as  $P(H)$  and  $P(H_i)$ .

□

$$P(H \setminus E) = P(H \setminus T) = P(H \setminus H_i) = P(E \setminus H_i).$$

So, from the "definition",

$$P(H \setminus H_i \setminus T) \leq P(H \setminus H_i).$$

measure on  $\mathcal{F}$ ) and  $H_i \subseteq H \setminus T$  which

$$\text{family in } \mathcal{F} \text{ with } P(H \setminus T) = P(H_i) \text{ (because } P \text{ is a}$$

and  $E \cap H_i = \emptyset$  if  $i \neq j$ . Well,  $(T_i)$  is a disjoint

$$\text{"easy": Let } (E_i) \text{ is * with } T_i \subseteq E_i \subseteq H_i, P(H_i) = 0,$$

That  $P$  is a countably additive set function on  $\mathcal{F}$ \*

$$\text{and } P(T_i) = P(T_i).$$

$$\text{and } P(T) = P(T \setminus T_i) + P(T_i)$$

$$\text{so } P(T) = P(T \setminus T_i) + P(T_i)$$

$$\text{and } T_i = T \setminus T_i \cup T_i,$$

$$T = T \setminus T_i \cup T_i$$

$$\text{so } P(T \setminus T_i) = 0.$$

$$T \setminus T_i \subseteq H \setminus T_i \text{ and } P(H \setminus T_i) = 0$$

then  $P(T \setminus T_i) = 0$ . Similarly,

$$T \setminus T_i \subseteq H_i \setminus T_i \text{ and } P(H_i \setminus T_i) = 0$$

$P(T_i)$ . We show they are equal: as

if we have two possible values for  $P(E)$ ,  $P(T)$  and

$T_i \subseteq E \subseteq H$ ,  $T_i, H_i \in \mathcal{F}$  with  $P(H_i \setminus T_i) = 0$ , on the fact

Measurable functions which agree on a set of probability measure reinforce the idea that one need only define a function on a set of probability one "to do integration theory". In fact this can be made precise. Define a function  $f$  to be "measurable on  $\Omega$ " if there is a set  $E \in \mathcal{F}$  with  $E(E) = 1$  and  $f$  is defined on  $E$  while  $f^{-1}(B) \cap E$  for every Borel set  $B \subseteq \mathbb{R}$ . First of all, it is obvious that any function measurable in the usual sense is measurable on  $\Omega$  instead any choice of  $E$  leaves the function unaffected the condition  $f$  to be  $\Omega$  on  $\Omega$  then we have a measurable function in the original sense. Should  $\mathbb{P}$  be complete then we can define  $f$  on  $\Omega$  in any way that we wish (note that each point in  $\Omega$  is - is, the singulation containing the point - also in  $\mathcal{F}$  if  $\mathbb{P}$  is complete). But the integral of  $f$  over any  $F \in \mathcal{F}$  is independent of how  $f$  might be defined on  $\Omega$ . So we don't need to specify how  $f$  is to be defined on  $\Omega$ , so long as we can define  $f$  on  $\Omega$  in either event that union also in  $\mathcal{F}$ .

Thus  $f^{-1}(\mathbb{R}) = f^{-1}(\mathbb{B}) \cup E \cup f^{-1}(\mathbb{B}) \cap (\Omega \setminus E)$ , the first set on the right side is in  $\mathcal{F}$  and the second is  $\emptyset$  if  $\mathbb{B}$  and  $\Omega \setminus E$  if  $\mathbb{B} \in \mathcal{E}$  in either event that union also in  $\mathcal{F}$ . It is all very well to define a function,  $f: \Omega \rightarrow [-\infty, \infty]$  as measurable on  $\Omega$ , but we are used to adding, multiplying, and so on, so is there a sensible way of adding such functions? Obviously, we could extend any part to all of  $\Omega$  in the manner described above (making them zero off their repective  $E$ 's) and then just add them as usual.

Extending the idea of measurable function:

One has to object that this runs against the spirit of the definition (if you're going to do this why bother---?). But observe if  $f_1, f_2$  are measurable on  $\mathcal{A}$ , with acts  $E_1, E_2$  & probability  $P$  for which  $P_{-}(B) \cap E_i \neq \emptyset$ ,  $E_1 \cap E_2$  &  $E_1 \cup E_2$ . So  $P(E_1 \cap E_2) \leq P(E_1) = P(E_2)$  and therefore  $P = P(E_1) = P(E_2)$ , obviously pointwise sum on  $E_1 \cap E_2$  we need only show that  $P(\mathcal{A} \setminus (E_1 \cap E_2)) = 0$ . If we define  $f_1 + f_2$  as their sum on  $E_1 \cap E_2$  we would be measurable on  $\mathcal{A}$ : Extend  $f_1$  and  $f_2$  to  $\mathcal{A}_1 \cup \mathcal{A}_2$  by setting them to be zero on  $\mathcal{A}_1 \setminus E_1$  and  $\mathcal{A}_2 \setminus E_2$  respectively. We know that " $f_1 + f_2$ " is measurable, that is our definition of sum, works. Notice also that if  $f$  is measurable on  $\mathcal{A}$  with  $P_{-}(B) \cap E \neq \emptyset$ , then  $f_{-}(B) \cap E \neq \emptyset$  and  $P(E \cap F) = 1$ . There is an overwhelming sense that another act of probability  $I$ , thus  $f_{-}(B) \cap E \cap F$  is determined by the relation  $f \sim g \Leftrightarrow f = g$  for all classes determined by the equivalence  $f \sim g \Leftrightarrow f = g$  for all sets we think of them as functions defined only on a set  $\mathcal{A}$ . It is these classes that become the objects of our study. There is a version of  $f$  defined on  $\mathcal{A}$ , and  $f$  defined on  $E \cap F$  are but versions of  $f$ . Thus is made precise by using the equivalence of  $f$ . This is made precise by using the equivalence  $f \sim g \Leftrightarrow f = g$  for all sets  $\mathcal{A}$ .

The has to object that this runs against the spirit of the definition (if you're going to do this why bother---?). But observe if  $f_1, f_2$  are measurable on  $\mathcal{A}$ , with acts  $E_1, E_2$  & probability  $P$  for which  $P_{-}(B) \cap E_i \neq \emptyset$ ,  $E_1 \cap E_2$  &  $E_1 \cup E_2$ . So  $P(E_1 \cap E_2) \leq P(E_1) = P(E_2)$ , thus  $P(\mathcal{A} \setminus (E_1 \cap E_2)) = 0$ . If we define  $f_1 + f_2$  as their sum on  $E_1 \cap E_2$  we would be measurable on  $\mathcal{A}$ : Extend  $f_1$  and  $f_2$  to  $\mathcal{A}_1 \cup \mathcal{A}_2$  by setting them to be zero on  $\mathcal{A}_1 \setminus E_1$  and  $\mathcal{A}_2 \setminus E_2$  respectively. We know that " $f_1 + f_2$ " is measurable, that is our definition of sum, works. Notice also that if  $f$  is measurable on  $\mathcal{A}$  with  $P_{-}(B) \cap E \neq \emptyset$ , then  $f_{-}(B) \cap E \neq \emptyset$  and  $P(E \cap F) = 1$ . There is an overwhelming sense that another act of probability  $I$ , thus  $f_{-}(B) \cap E \cap F$  is determined by the relation  $f \sim g \Leftrightarrow f = g$  for all sets we think of them as functions defined only on a set  $\mathcal{A}$ . It is these classes that become the objects of our study. There is a version of  $f$  defined on  $\mathcal{A}$ , and  $f$  defined on  $E \cap F$  are but versions of  $f$ . Thus is made precise by using the equivalence  $f \sim g \Leftrightarrow f = g$  for all sets  $\mathcal{A}$ .