

Introduction to Recursive Filtering and Estimation

Spring 2010

Problem Set:
Probability review

Notes:

- **Notation:** Unless otherwise noted, x , y , and z denote random variables, $f_x(x)$ (or the short hand $f(x)$) denotes the probability density function of x , and $f_{x|y}(x|y)$ (or $f(x|y)$) denotes the conditional probability density function of x conditioned on y . The expected value is denoted by $E[\cdot]$, the variance is denoted by $\text{Var}(\cdot)$ and $\Pr(Z)$ denotes the probability that the event Z occurs.
- Please report any error that you may find to the teaching assistants (strimpe@ethz.ch or aschoellig@ethz.ch).

Problem Set

Problem 1

Prove $f(x|y) = f(x) \Leftrightarrow f(y|x) = f(y)$.

Problem 2

Prove $f(x|y, z) = f(x|z) \Leftrightarrow f(x, y|z) = f(x|z)f(y|z)$.

Problem 3

Come up with an example where $f(x, y|z) = f(x|z)f(y|z)$ but $f(x, y) \neq f(x)f(y)$ for *continuous* random variables x , y , and z .

Problem 4

Come up with an example where $f(x, y|z) = f(x|z)f(y|z)$ but $f(x, y) \neq f(x)f(y)$ for *discrete* random variables x , y , and z .

Problem 5

Let x and y be binary random variables: $x, y \in \{0, 1\}$. Prove that $f_{x,y}(x, y) \geq f_x(x) + f_y(y) - 1$, which is called *Bonferroni's inequality*.

Problem 6

Prove $E[ax + b] = aE[x] + b$, where a and b are constants.

Problem 7

Let x and y be scalar random variables. Prove that for any functions $g(\cdot)$ and $h(\cdot)$, $E[g(x)h(y)] = E[g(x)]E[h(y)]$ if x and y are independent.

Problem 8

From above, it follows that if x and y are independent, then $E[xy] = E[x]E[y]$. Is the converse true, that is, if $E[xy] = E[x]E[y]$, does it imply that x and y are independent? If yes, prove it. If no, find a counter-example.

Problem 9

Let $x \in \mathcal{X}$ be a scalar valued continuous random variable and $g(x)$ a continuously differentiable, strictly monotonically increasing function. Prove the *law of the unconscious statistician*, that is, show that the expected value of $y = g(x)$ is given by

$$E[y] = \int_{x \in \mathcal{X}} g(x) f_x(x) dx.$$

Problem 10

Let y be a scalar continuous random variable with probability density function $f_y(y)$, and g be a function transforming y to a new variable x by $x = g(y)$. Prove the *change of variables formula*, i.e. the equation for the probability density function $f_x(x)$, under the assumption that g is continuously differentiable with $\frac{dg(y)}{dy} < 0 \forall y$.

Problem 11

Let $x \in \mathcal{X}$ and $y \in \mathcal{Y}$ be independent, scalar valued discrete random variables. Let $z = x + y$. Prove that

$$f_z(z) = \sum_{y \in \mathcal{Y}} f_x(z - y) f_y(y) = \sum_{x \in \mathcal{X}} f_x(x) f_y(z - x),$$

thus the probability density function is the *convolution* of the individual probability density functions.

Problem 12

Let x be a scalar continuous random variable that takes on only non-negative values. Prove that, for $a > 0$,

$$\Pr(x \geq a) \leq \frac{\mathbb{E}[x]}{a},$$

which is called *Markov's inequality*.

Problem 13

Let x be a scalar continuous random variable. Let $\bar{x} = \mathbb{E}[x]$, $\sigma^2 = \text{Var}(x)$. Prove that for any $k > 0$,

$$\Pr(|x - \bar{x}| \geq k) \leq \frac{\sigma^2}{k^2},$$

which is called *Chebyshev's inequality*.

Problem 14

Let $x_1, x_2, \dots, x_n$ be independent random variables, each having a uniform distribution over $[0, 1]$. Let $m = \max\{x_1, x_2, \dots, x_n\}$. Show that the cumulative distribution function of m , $F_m(\cdot)$, is given by

$$F_m(m) = m^n, \quad 0 \leq m \leq 1.$$

What is the probability density function of m ?

Problem 15

Prove that $\mathbb{E}[x^2] \geq (\mathbb{E}[x])^2$. When do we have equality?

Problem 16

Suppose that x and y are independent scalar continuous random variables. Show that

$$\Pr(x \leq y) = \int_{-\infty}^{\infty} F_x(y) f_y(y) dy.$$

Problem 17

Use Chebyshev's inequality to prove the *weak law of large numbers*. Namely, if $x_1, x_2, \dots$ are independent and identically distributed with mean μ and variance σ^2 then, for any $\varepsilon > 0$,

$$\Pr\left(\left|\frac{x_1 + x_2 + \dots + x_n}{n} - \mu\right| > \varepsilon\right) \rightarrow 0 \quad \text{as } n \rightarrow \infty.$$

Problem 18

Suppose that x is a random variable with mean 10 and variance 15. What can we say about $\Pr(5 < x < 15)$?

Problem 19

Let x and y be independent random variables with means μ_x and μ_y and variances σ_x^2 and σ_y^2 . Show that

$$\text{Var}(xy) = \sigma_x^2 \sigma_y^2 + \mu_y^2 \sigma_x^2 + \mu_x^2 \sigma_y^2.$$

Problem 20

a) Use the method presented in class to obtain samples x of the *exponential distribution*

$$\hat{f}_x(x) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & x < 0 \end{cases}$$

from given samples u of a uniform distribution.

b) Exponential random variables are used to model failures of components that do not wear, for example solid state electronics. This is based on their property

$$\Pr(x > s + t | x > t) = \Pr(x > s) \quad \forall s, t \geq 0.$$

A random variable with this property is said to be *memoryless*. Prove that a random variable with an exponential distribution satisfies this property.

Problem Set 1: Recursive Filtering & Estimation

Probability Review

Problem 1

- from definition of conditional probability, we have

$$f(x, y) = f(x|y) f(y) \quad \text{and} \quad f(x, y) = f(y|x) f(x)$$

and therefore $f(x|y) f(y) = f(y|x) f(x)$ (*)

- If $f(x|y) = f(x)$ $\stackrel{(*)}{\Rightarrow} f(x) f(y) = f(y|x) f(x)$
 $\Rightarrow f(y) = f(y|x)$

- If $f(y|x) = f(y)$ $\stackrel{(*)}{\Rightarrow} f(x|y) f(y) = f(y) f(x)$
 $\Rightarrow f(x) = f(x|y)$

$$\therefore f(x|y) = f(x) \Leftrightarrow f(y|x) = f(y) \quad \text{q.e.d.}$$

Problem 2

Follows directly from $f(x, y|z) = f(x|y, z) f(y|z)$

Problem 3]

- Let $x, y, z \in [0, 1]$ be continuous random variables.
- Consider joint pdf $f(x, y, z) = c \cdot g_x(x, z) g_y(y, z)$ where g_x and g_y are functions (not necessarily pdf's) and c is a constant such that

$$\int_0^1 \int_0^1 \int_0^1 f(x, y, z) dx dy dz = 1$$

Then

$$f(x, y | z) = \frac{f(x, y, z)}{f(z)} = \frac{c \cdot g_x(x, z) g_y(y, z)}{c \cdot G_x(z) \cdot G_y(z)},$$

with

$$G_x(z) = \int_0^1 g_x(x, z) dx, \quad G_y(z) = \int_0^1 g_y(y, z) dy$$

$$\begin{aligned} \text{(since } f(z) &= \int_0^1 \int_0^1 c g_x(x, z) g_y(y, z) dx dy \\ &= c \int_0^1 G_x(z) \cdot g_y(y, z) dy = c G_x(z) \cdot G_y(z) \text{.)} \end{aligned}$$

Also

$$\begin{aligned} f(x | z) &= \frac{f(x, z)}{f(z)} = \frac{\int_0^1 f(x, y, z) dy}{f(z)} = \frac{c \cdot g_x(x, z) G_y(z)}{c \cdot G_x(z) G_y(z)} \\ &= \frac{g_x(x, z)}{G_x(z)} \end{aligned}$$

$$f(y | z) = \frac{g_y(y, z)}{G_y(z)} \quad (\text{by analogy})$$

$$\text{Therefore, } f(x, y | z) = \frac{g_x(x, z) g_y(y, z)}{G_x(z) G_y(z)} = f(x | z) \cdot f(y | z).$$

- Now, let $g_x(x, z) = x + z$ and $g_y(y, z) = y + z$.

Then

$$\begin{aligned} f(x, y) &= \int_0^1 f(x, y, z) dz = c \int_0^1 (x+z)(y+z) dz \\ &= c \int_0^1 z^2 + (x+y)z + xy dz = c \left[\frac{1}{3} z^3 + \frac{1}{2} (x+y) z^2 + xy z \right]_{z=0}^{z=1} \\ &= c \left(\frac{1}{3} + \frac{1}{2} (x+y) + xy \right) \end{aligned}$$

$$f(x) = \int_0^1 f(x,y) dx = c \int_0^1 \left(\frac{1}{3} + \frac{1}{2}x + \frac{1}{2}y + xy \right) dx$$

$$= c \left(\frac{1}{3} + \frac{1}{4} + \frac{1}{2}y + \frac{1}{2}y \right) = c \left(y + \frac{7}{12} \right)$$

$$f(y) = \int_0^1 f(x,y) dy = c \left(x + \frac{7}{12} \right) \quad (\text{by symmetry})$$

Therefore, $f(x)f(y) = c^2 \left(\frac{49}{144} + \frac{7}{12}(x+y) + xy \right) \neq f(x,y).$

Problem 4

• As in problem 3, let $f(x,y,z) = c g_x(x,z) g_y(y,z)$. This ensures $f(x,y|z) = f(x|z)f(y|z)$. Let $x,y,z \in \{0,1\}$

• Define g_x and g_y by value tables:

x	z	$g_x(x,z)$
0	0	0
0	1	1
1	0	1
1	1	0

y	z	$g_y(y,z)$
0	0	1
0	1	0
1	0	0
1	1	1

x	y	z	$f(x,y,z) = \frac{1}{2} g_x(x,z) g_y(y,z)$
0	0	0	0
0	0	1	0
0	1	0	0
0	1	1	0.5
1	0	0	0.5
1	0	1	0
1	1	0	0
1	1	1	0

- Compute $f(x,y)$, $f(x)$, $f(y)$

x	y	$f(x,y)$
0	0	0
0	1	0.5
1	0	0.5
1	1	0

x	$f(x)$
0	0.5
1	0.5

y	$f(y)$
0	0.5
1	0.5

x	y	$f(x)f(y)$
0	0	0.25
0	1	0.25
1	0	0.25
1	1	0.25

$$\left(\begin{aligned} f(x,y) &= \sum_z f(x,y,z) = f(x,y,0) + f(x,y,1) \\ f(x) &= f(x,0) + f(x,1) \end{aligned} \right)$$

$$\therefore f(x,y) \neq f(x)f(y)$$

- Its verification, compute $f(x,y|z)$, $f(x|z)$, $f(y|z)$, although by construction of $f(x,y,z)$ it is already clear that $f(x,y|z) = f(x|z)f(y|z)$.

x	y	z	$f(x,y z)$
0	0	0	0
0	1	0	0
1	0	0	1
1	1	0	0
0	0	1	0
0	1	1	1
1	0	1	0
1	1	1	0

From $f(x,y,z)$ it follows that
if $z=0$, then $(x,y)=(1,0)$
with probability 1

$$\text{(or: compute from } f(x,y|z) = \frac{f(x,y,z)}{f(z)}$$

similarly

x	z	$f(x z)$
0	0	0
1	0	1
0	1	1
1	1	0

y	z	$f(y z)$
0	0	1
1	0	0
0	1	0
1	1	1

x	y	z	$f(x z)f(y z)$
0	0	0	0
0	1	0	0
1	0	0	1
1	1	0	0
0	0	1	0
0	1	1	1
1	0	1	0
1	1	1	0

Problem 5

- By marginalization,

$$f_x(x) = \sum_{y \in Y} f_{xy}(x, y) = f_{xy}(x, y) + f_{xy}(x, 1-y)$$

$$f_y(y) = \sum_{x \in X} f_{xy}(x, y) = f_{xy}(x, y) + f_{xy}(1-x, y)$$

- Therefore,

$$f_x(x) + f_y(y) = 2 f_{xy}(x, y) + f_{xy}(x, 1-y) + f_{xy}(1-x, y)$$

$$= \underbrace{f_{xy}(x, y) + f_{xy}(x, 1-y) + f_{xy}(1-x, y) + f_{xy}(1-x, 1-y)}_{= 1}$$

$$= \sum_{y \in \{0,1\}} \sum_{x \in \{0,1\}} f_{xy}(x, y) = 1$$

$$- f_{xy}(1-x, 1-y) + f_{xy}(x, y)$$

$$= 1 + f_{xy}(x, y) - f_{xy}(1-x, 1-y)$$

$$\leq 1 + f_{xy}(x, y)$$

$$\Rightarrow f_{xy}(x, y) \geq f_x(x) + f_y(y) - 1$$

q.e.d.

Problem 6

Using the law of the unconscious statistician, we have for a discrete random variable x

$$\begin{aligned} E[ax+b] &= \sum_{x \in X} (ax+b) f_x(x) dx = a \underbrace{\sum_{x \in X} x f_x(x)}_{E[x]} + b \underbrace{\sum_{x \in X} f_x(x)}_1 \\ &= a E[x] + b \end{aligned}$$

and for a continuous random variable x

$$\begin{aligned} E[ax+b] &= \int_{-\infty}^{\infty} (ax+b) f_x(x) dx \\ &= a \underbrace{\int_{-\infty}^{\infty} x f_x(x) dx}_{E[x]} + b \underbrace{\int_{-\infty}^{\infty} f_x(x) dx}_1 \\ &= a E[x] + b \end{aligned}$$

q.e.d.

Problem 7

Using the law of the unconscious statistician applied on the vector random variable $\begin{bmatrix} x \\ y \end{bmatrix}$ with pdf $f_{xy}(x,y)$, we have

$$\begin{aligned} E[g(x)h(y)] &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x)h(y) f_{xy}(x,y) dx dy \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x)h(y) f_x(x) f_y(y) dx dy \\ &= \int_{-\infty}^{\infty} g(x) f_x(x) dx \cdot \int_{-\infty}^{\infty} h(y) f_y(y) dy \quad (\text{By independence } x,y) \\ &= E[g(x)] \cdot E[h(y)]. \end{aligned}$$

and similarly for discrete random variables.

Problem 8

We will construct a counterexample.

- Let x be a discrete r.v. that takes the values $-1, 0$, and 1 with probabilities $\frac{1}{4}, \frac{1}{2}$, and $\frac{1}{4}$, respectively.
- Let y be a discrete r.v. taking the values $-1, 1$ with equal probability. Let x and y be independent.
- Let z be a discrete r.v. defined by $z = x \cdot y$.[⊕] By construction, it is clear that z depends on x . We will show that

$$E[xz] = E[x] \cdot E[z].$$

⊕ It follows that z can take the values $-1, 0, 1$.

Pdf $f_{xz}(x,z)$:

x	z	$f_{xz}(x,z)$	
-1	-1	$1/8$	$\rightarrow x=-1 \text{ (Prob } \frac{1}{4}) \wedge w=1 \text{ (Prob } \frac{1}{2})$
-1	0	0	$\rightarrow$ impossible since $w \neq 0$
-1	1	$1/8$	$\rightarrow x=-1 \text{ (Prob } \frac{1}{4}) \wedge w=-1 \text{ (Prob } \frac{1}{2})$
0	-1	0	$\rightarrow$ impossible
0	0	$1/2$	$\rightarrow w \text{ either } \pm 1, x=0 \text{ (Prob } \frac{1}{2})$
0	1	0	$\vdots$
1	-1	$1/8$	
1	0	0	
1	1	$1/8$	

Marginalization: $f_x(x), f_z(z)$

x	$f(x)$		z	$f(z)$
-1	$1/4$		-1	$1/4$
0	$1/2$		0	$1/2$
1	$1/4$ ✓		1	$1/4$ ✓

It follows that $f_{xz}(x,z) = f_x(x) f_z(z) \forall x,z$ does not hold.
For example, $f_{xz}(-1,0) = 0 \neq 1/8 = f_x(-1) f_z(0)$

Expected values:

$$\begin{aligned} E[xz] &= \sum_x \sum_z xz f_{xz}(x,z) \\ &= (-1)(-1) \frac{1}{8} + (-1)(1) \frac{1}{8} + 0 \cdot 0 \cdot \frac{1}{2} + (1)(-1) \cdot \frac{1}{8} + (1)(1) \frac{1}{8} \\ &= 0 \end{aligned}$$

$$\begin{aligned} E[x] &= \sum_x x f_x(x) \\ &= -\frac{1}{4} + \frac{1}{4} = 0 \end{aligned}$$

$$E[z] = 0$$

$$\therefore E[xz] = E[x] E[z] \not\Rightarrow f_{xz}(x,z) = f_x(x) \cdot f_z(z)$$

Problem 9

- From the change of variables formula (see problem 10), we have

$$f_Y(y) = \frac{f_X(x)}{\frac{dg}{dx}(x)} \quad (\text{since } g \text{ cont differentiable, strictly monotonic})$$

- Furthermore, $y = g(x) \Rightarrow dy = \frac{dg}{dx}(x) dx$

- Let $Y = g(X)$, that is $Y = \{y \mid \exists x \in X: y = g(x)\}$.

$$\begin{aligned} E[Y] &= \int_{y \in Y} y f_Y(y) dy = \int_{x \in X} g(x) \frac{f_X(x)}{\frac{dg}{dx}(x)} \frac{dg}{dx}(x) dx \\ &= \int_{x \in X} g(x) f_X(x) dx \end{aligned} \quad \text{g.c.d}$$

Problem 10

- Consider the probability that y is in a small interval $[\bar{y}, \bar{y} + \Delta y]$ (with $\Delta y > 0$ small),

$$P(Y \in [\bar{y}, \bar{y} + \Delta y]) = \int_{\bar{y}}^{\bar{y} + \Delta y} f_Y(y) dy$$

which approaches $f_Y(\bar{y}) \Delta y$ in the limit as $\Delta y \rightarrow 0$

- Let $\bar{x} := g(\bar{y})$. For small Δy , we have (Taylor series)

$$g(\bar{y} + \Delta y) \approx g(\bar{y}) + \underbrace{\frac{dg}{dy}(\bar{y}) \cdot \Delta y}_{=:\Delta x} = \bar{x} + \Delta x, \quad \Delta x < 0 \quad (*)$$

- We are interested in the probability that $x \in [\bar{x} + \Delta x, \bar{x}]$.

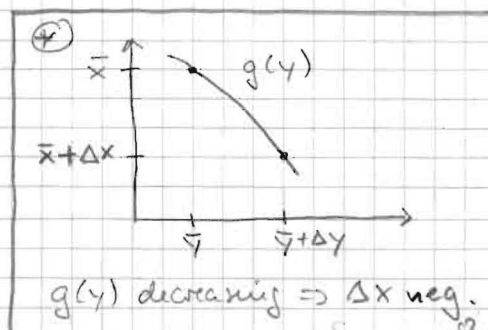
For small Δx , this probability is equal the probability that

$y \in [\bar{y}, \bar{y} + \Delta y]$ (since $y \in [\bar{y}, \bar{y} + \Delta y] \Rightarrow g(y) \in [g(\bar{y}), g(\bar{y} + \Delta y)] \Rightarrow x \in [\bar{x} + \Delta x, \bar{x}]$ for small Δy and Δx).

$$\therefore P(Y \in [\bar{y}, \bar{y} + \Delta y]) = f_Y(\bar{y}) \Delta y$$

$$= P(X \in [\bar{x} + \Delta x, \bar{x}]) = -f_X(\bar{x}) \Delta x$$

for small Δy (and thus small Δx)



$$\Rightarrow f_Y(\bar{y}) \Delta y = -f_X(\bar{x}) \Delta x$$

$$\Rightarrow f_X(\bar{x}) = \frac{f_Y(\bar{y})}{-\frac{\Delta x}{\Delta y}}$$

As $\Delta y \rightarrow 0$ (and thus $\Delta x \rightarrow 0$), $\frac{\Delta x}{\Delta y} \rightarrow + \frac{dg}{dy}(\bar{y})$ and therefore

$$f_X(\bar{x}) = \frac{f_Y(\bar{y})}{-\frac{dg}{dy}(\bar{y})}$$

or

$$f_X(x) = \frac{f_Y(y)}{-\frac{dg}{dy}(y)}.$$

Problem 11

$$\bullet f_Z(\bar{z}) = \Pr\{Z = \bar{z}\}$$

The probability that Z takes on $\bar{z}$ is given by the sum of the probabilities of all possible combinations of x and y such that $\bar{z} = x + y$, that is all $\bar{y} \in Y$ s.t. $x = \bar{z} - \bar{y}$ and $y = \bar{y}$ [or alternatively, $\bar{x} \in X$ s.t. $x = \bar{x}$ and $y = \bar{z} - \bar{x}$].

$$\begin{aligned} \therefore f_Z(\bar{z}) = \Pr\{Z = \bar{z}\} &= \sum_{\bar{y} \in Y} \Pr\{x = \bar{z} - \bar{y}\} \cdot \Pr\{y = \bar{y}\} \quad (\text{by independence assumption}) \\ &= \sum_{\bar{y} \in Y} f_X(\bar{z} - \bar{y}) f_Y(\bar{y}) \end{aligned}$$

$$\text{Rewrite } f_Z(z) = \sum_{y \in Y} f_X(z - y) f_Y(y)$$

$$\text{Similarly, } f_Z(z) = \sum_{x \in X} f_X(x) f_Y(z - x).$$

g.e.d.

Problem 12

$$\begin{aligned} E[X] &= \int_0^{\infty} x f(x) dx = \underbrace{\int_0^a x f(x) dx}_{\geq 0} + \int_a^{\infty} x f(x) dx \\ &\geq \int_a^{\infty} x f(x) dx \geq \int_a^{\infty} a f(x) dx \\ &= a \int_a^{\infty} f(x) dx = a \Pr(X \geq a) \end{aligned}$$

q.e.d.

Problem 13

Can be obtained as a corollary of Markov's inequality:

- $(x - \bar{x})^2$ is a nonnegative random variable; apply Markov's inequality with $a = k^2$ ($k > 0$):

$$\Pr((x - \bar{x})^2 \geq k^2) \leq \frac{E[(x - \bar{x})^2]}{k^2} = \frac{\text{Var}(x)}{k^2} = \frac{\sigma^2}{k^2}$$

- Since $(x - \bar{x})^2 \geq k^2 \Leftrightarrow |x - \bar{x}| \geq k$,

$$\Pr(|x - \bar{x}| \geq k) \leq \frac{\sigma^2}{k^2}$$

q.e.d.

Problem 14

For $0 \leq t \leq 1$,

$$\begin{aligned} F_m(t) &= \Pr(m \in [0, t]) = \Pr(\max\{x_1, \dots, x_n\} \in [0, t]) \\ &= \Pr(x_i \in [0, t] \forall i \in \{1, \dots, n\}) \\ &= \Pr(x_1 \in [0, t]) \cdot \Pr(x_2 \in [0, t]) \cdot \dots \cdot \Pr(x_n \in [0, t]) \\ &= t^n \quad (\text{with } t=m \rightarrow F_m(m) = m^n) \end{aligned}$$

$$\text{Since } F_m(m) = \int_0^m f_m(z) dz,$$

$$f_m(m) = \frac{dF_m}{dm}(m) = \frac{d}{dm}(m^n) = n \cdot m^{n-1}.$$

Problem 15

Let $\bar{x} = E[x]$.

$$\begin{aligned}\text{Var}(x) &= \int_{-\infty}^{\infty} (x - \bar{x})^2 f(x) dx = \int_{-\infty}^{\infty} x^2 f(x) dx - 2\bar{x} \underbrace{\int_{-\infty}^{\infty} x f(x) dx}_{\bar{x}} + \bar{x}^2 \underbrace{\int_{-\infty}^{\infty} f(x) dx}_1 \\ &= E[x^2] - 2\bar{x}^2 + \bar{x}^2 = E[x^2] - \bar{x}^2\end{aligned}$$

$$\therefore E[x^2] = \bar{x}^2 + \text{Var}(x)$$

$$\geq \bar{x}^2$$

(since $\text{Var}(x) \geq 0$)

with equality if $\text{Var}(x) = 0$, i.e. when x is constant.

Problem 16

• For fixed $\bar{y} \in Y$,

$$\Pr(x \leq \bar{y}) = F_x(\bar{y})$$

• The probability that $y \in [\bar{y}, \bar{y} + \Delta y]$ is

$$\Pr(y \in [\bar{y}, \bar{y} + \Delta y]) = \int_{\bar{y}}^{\bar{y} + \Delta y} f_y(y) dy \rightarrow f_y(\bar{y}) \cdot \Delta y \text{ for small } \Delta y$$

• Therefore, the probability that $x \leq \bar{y}$ and $y \in [\bar{y}, \bar{y} + \Delta y]$ is

$$\begin{aligned}\Pr(x \leq \bar{y} \wedge y \in [\bar{y}, \bar{y} + \Delta y]) &= \Pr(x \leq \bar{y}) \cdot \Pr(y \in [\bar{y}, \bar{y} + \Delta y]) \\ &= F_x(\bar{y}) \cdot f_y(\bar{y}) \Delta y \quad (*) \quad (\text{by indep. of } x, y)\end{aligned}$$

• Now, since we are interested in $\Pr(x \leq y)$, i.e. in the probability of x being less than any y and not just a fixed $\bar{y}$, we can sum (*) over all possible intervals $[\bar{y}_i, \bar{y}_i + \Delta y]$

$$\Pr(\exists \bar{y}_i \text{ such that } x \leq \bar{y}_i) = \sum_{i=-\infty}^{\infty} F_x(\bar{y}_i) \cdot f_y(\bar{y}_i) \cdot \Delta y$$

By letting $\Delta y \rightarrow 0$, we obtain

$$\Pr(x \leq y) = \int_{-\infty}^{\infty} F_x(y) f_y(y) dy.$$

Problem 17

- Consider the random variable $\frac{x_1 + x_2 + \dots + x_n}{n}$.
It has the mean

$$E\left[\frac{x_1 + x_2 + \dots + x_n}{n}\right] = \frac{1}{n} (E[x_1] + \dots + E[x_n]) = \frac{1}{n} (n\mu) = \mu$$

and variance

$$\begin{aligned} \text{Var}\left(\frac{x_1 + x_2 + \dots + x_n}{n}\right) &= E\left[\left(\frac{x_1 + x_2 + \dots + x_n}{n} - \mu\right)^2\right] \\ &= \frac{1}{n^2} \left(E[(x_1 - \mu)^2] + \dots + E[(x_n - \mu)^2] + \text{"cross terms"} \right) \end{aligned}$$

where the expected value of the cross terms is zero,
for example,

$$\begin{aligned} E[(x_i - \mu)(x_j - \mu)] &= E[x_i - \mu] \cdot E[x_j - \mu] \text{ for } i \neq j, \text{ by independence} \\ &= 0 \end{aligned}$$

$$\therefore \text{Var}\left(\frac{x_1 + x_2 + \dots + x_n}{n}\right) = \frac{1}{n^2} (\text{Var}(x_1) + \dots + \text{Var}(x_n)) = \frac{n\sigma^2}{n^2} = \frac{\sigma^2}{n}$$

- Applying Chebyshev's inequality with $\epsilon > 0$.

$$\Pr\left(\left|\frac{x_1 + x_2 + \dots + x_n}{n} - \mu\right| \geq \epsilon\right) \leq \frac{\sigma^2}{n\epsilon^2} \rightarrow 0 \text{ as } n \rightarrow \infty$$

$$\Rightarrow \Pr\left(\left|\frac{x_1 + x_2 + \dots + x_n}{n} - \mu\right| > \epsilon\right) \rightarrow 0 \text{ as } n \rightarrow \infty$$

$$\left[\begin{aligned} \text{Note: } \Pr\left(\left|\frac{x_1 + \dots + x_n}{n} - \mu\right| \geq \epsilon\right) &= \\ &= \Pr\left(\left|\frac{x_1 + \dots + x_n}{n} - \mu\right| > \epsilon\right) + \underbrace{\Pr\left(\left|\frac{x_1 + \dots + x_n}{n} - \mu\right| = \epsilon\right)}_{=0 \text{ since } \frac{x_1 + \dots + x_n}{n} \text{ is a continuous random variable}} \end{aligned} \right]$$

Problem 18

- $\Pr(5 < x < 15)$
 $= \Pr(|x - 10| < 5) = 1 - \Pr(|x - 10| \geq 5)$
- Chebyshev's inequality with $\bar{x} = 10$, $\sigma^2 = 15$, $k = 5$
 $\Pr(|x - 10| \geq 5) \leq \frac{15}{5^2} = \frac{15}{25} = \frac{3}{5}$
- $\therefore \Pr(5 < x < 15) \geq 1 - \frac{3}{5} = \frac{2}{5}$

Problem 19

- Mean: $E[xy] = E[x] \cdot E[y] = \mu_x \mu_y$
- $\text{Var}(xy) = E[(xy)^2] - (\mu_x \mu_y)^2$
 $= E[x^2] E[y^2] - \mu_x^2 \mu_y^2$
- Using $E[x^2] = \sigma_x^2 + \mu_x^2$ and $E[y^2] = \sigma_y^2 + \mu_y^2$, we have
$$\begin{aligned} \text{Var}(xy) &= (\sigma_x^2 + \mu_x^2)(\sigma_y^2 + \mu_y^2) - \mu_x^2 \mu_y^2 \\ &= \sigma_x^2 \sigma_y^2 + \mu_y^2 \sigma_x^2 + \mu_x^2 \sigma_y^2 \end{aligned}$$

g.c.d.

Problem 20

a). cumulative distribution:

$$\hat{F}_x(x) = \int_0^x \lambda e^{-\lambda t} dt = \left[-e^{-\lambda t} \right]_{t=0}^x = 1 - e^{-\lambda x}$$

- u : sample from uniform distribution. According to method presented in class, obtain sample x by solving $u = \hat{F}_x(x)$ for x :

$$u = 1 - e^{-\lambda x} \quad \Leftrightarrow \quad e^{-\lambda x} = 1 - u$$

$$\Leftrightarrow -\lambda x = \ln(1 - u)$$

$$\Leftrightarrow \underline{\underline{x = \frac{-\ln(1-u)}{\lambda}}}$$

$$\bullet \quad u \rightarrow 0 \Rightarrow x \rightarrow 0,$$

$$u \rightarrow 1 \Rightarrow x \rightarrow +\infty$$

b)

$$\Pr(x > s+t \mid x > t)$$

$$= \frac{\Pr(x > s+t \wedge x > t)}{\Pr(x > t)} = \frac{\Pr(x > s+t)}{\Pr(x > t)}$$

$$= \frac{\int_{s+t}^{\infty} \lambda e^{-\lambda x} dx}{\int_t^{\infty} \lambda e^{-\lambda x} dx} = \frac{\left[-e^{-\lambda x} \right]_{s+t}^{\infty}}{\left[-e^{-\lambda x} \right]_t^{\infty}} = \frac{e^{-\lambda(s+t)}}{e^{-\lambda t}}$$

$$= e^{-\lambda s} = \int_s^{\infty} \lambda e^{-\lambda x} dx$$

$$= \Pr(x > s)$$

q.e.d.