

## Important Announcements

- assignment 1 is due this Friday ( Jan 24 )
- review session by TA on Monday

Arthritis Young

$\frac{1}{2}$ $(0,0)$	$\frac{1}{100} (1,0)$ $\frac{39}{100} (1,1)$
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$\frac{1}{100} (0,1)$

condition on being young

$Y=0$ $\frac{50}{51}$
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$\frac{1}{51}, Y=1$

$$\begin{aligned}
 &= P_{Y|X}(1|0) \\
 &= \frac{P_{xy}(0,1)}{P_X(0)} \\
 &= \frac{P(0,1)}{P(0,1) + P(0,0)} \\
 &= \frac{1/100}{1/100 + 1/2} \\
 &= \frac{1/100}{51/100} = \frac{1}{51}
 \end{aligned}$$

product rule from above  
 $P(x,y) = P(x|y)P(y)$

Ex: Probability of being young given I have arthritis

$$P(X=0|Y=1) = P_{X|Y}(0|1)$$

Bayes' Rule

$$\begin{aligned}
 &= \frac{P_{Y|X}(1|0) P_X(0)}{P_Y(1)} \\
 &= \frac{\frac{1}{51} \frac{51}{100}}{40/100} = \frac{1}{40}
 \end{aligned}$$

Independence: Changing the value of one r.v. doesn't affect the probability of another r.v.

r.v.  $X, Y$  are independent if:  $p(x, y) = p(x)p(y)$

Since  $p(x, y) = p(x|y)p(y) = p(x)p(y|x) = p(x)p(y)$

independence implies:  $p(x|y) = p(x)$ ,  $p(y|x) = p(y)$

More generally:

$X_1, X_2, \dots, X_d$  are independent if:  $p(x_1, \dots, x_d) = p(x_1) \cdots p(x_d)$

Similarly for distributions:

r.v.  $X, Y$  are independent if:  $P(X \in E_x, Y \in E_y) = P(X \in E_x)P(Y \in E_y)$

$E_x$ :  $X, Y$  are not independent for Arthritis ex

$$p(0, 1) = \frac{1}{100} \neq p_x(0)p_y(1) = \frac{51}{100} \frac{40}{100} = 0.204$$

$E_x$ :  $X_1, X_2 \in \{0, 1\}$  are flips of two different fair coins

$$p(x_1, x_2) = \frac{1}{4} \text{ for all } x_1 \in \mathcal{X}_1, x_2 \in \mathcal{X}_2$$

$$p_{x_1}(x_1)p_{x_2}(x_2) = \frac{1}{2} \frac{1}{2} = \frac{1}{4}$$

		$X_2$	
		H	T
$X_1$	H	$\frac{1}{4}$	$\frac{1}{4}$
	T	$\frac{1}{4}$	$\frac{1}{4}$

What happens when  $Z=(X,Y)$  with  $Y$  discrete and  $X$  continuous?

$p: \mathcal{X} \times \mathcal{Y} \rightarrow ?$  pmf or pdf? **Ans: neither**

Instead we will write  $p(x,y)$  in terms of a marginal pdf for  $X$  and a conditional pmf for  $Y|X$

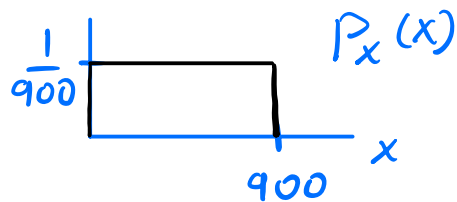
$$p(x,y) = p_X(x) p_{Y|X}(y|x) \quad \text{product rule}$$

where  $p_{Y|X=x}: \mathcal{Y} \rightarrow [0,1]$  is a pmf

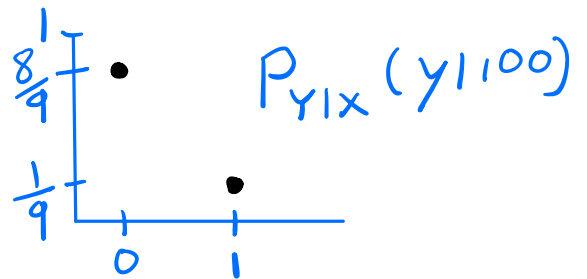
$p_X(x): \mathcal{X} \rightarrow [0,\infty)$  is a pdf

$E_x$ :  $X \in \mathcal{X} = [0, 900]$ ,  $Y \in \mathcal{Y} = \{0, 1\}$   $\leftarrow$  Barolo

pdf:  $p_X = \text{Uniform}(0, 900)$   
 $= \frac{1}{900}$



$p_{Y|X=x} = \text{Bernoulli}(\frac{x}{900})$



pmf:  $p_{Y|X}(y|x) = \begin{cases} \frac{x}{900} & \text{if } y=1 \\ 1 - \frac{x}{900} & \text{if } y=0 \end{cases}$   
Defn of Bernoulli( $\frac{x}{900}$ )

$$\begin{aligned} P(X \in [0, 50], Y=1) &= \int_0^{50} \left( \sum_{y \in \{1\}} p(y, x) \right) dx \\ &= \int_0^{50} \left( \sum_{y \in \{1\}} p_{Y|X}(y|x) p_X(x) \right) dx \end{aligned}$$

$$= \int_0^{50} p_{YX}(1|x) p_X(x) dx$$

$$= \int_0^{50} \frac{x}{900} \frac{1}{900} dx$$

$$= \frac{1}{810000} \frac{x^2}{2} \Big|_0^{50}$$

$$= \frac{1}{810000} \frac{2500}{2}$$

$$= \frac{1}{648} \quad 0.154\%$$

# Representing Random Features, Labels, and Datasets

## Random variables:

$$D = (Z_1, Z_2, \dots, Z_n) \in \mathcal{Z}_1 \times \dots \times \mathcal{Z}_n = \mathcal{Z}^n \quad \text{since } \mathcal{Z} = \mathcal{Z}_1 = \dots = \mathcal{Z}_n$$

$$Z_i = (\vec{X}_i, Y_i) \in \mathcal{X} \times \mathcal{Y} = \mathcal{Z} \quad \text{each } Z_i \text{ is a feature-label pair}$$

$$\vec{X}_i = (X_{i,1}, \dots, X_{i,d})^T \in \mathbb{R}^d = \mathcal{X} \quad \vec{X}_i \text{ is a feature vector}$$

## Distributions:

$P_D$ : distribution for  $D$ ,  $P_{Z_i}$ : marginal distribution for  $Z_i$

assumptions:

1.  $(\vec{X}_i, Y_i) = Z_i$  are independent for all  $i \in \{1, \dots, n\}$
2.  $P_{Z_1} = P_{Z_2} = \dots = P_{Z_n} = P_Z$  all  $Z_i$  have the same distribution  
“( $\vec{X}_i, Y_i$ ) are independent and identically distributed (i.i.d)”

$$\begin{aligned} P_D(Z_1 \in \mathcal{E}_1, \dots, Z_n \in \mathcal{E}_n) &= P_{Z_1}(Z_1 \in \mathcal{E}_1) \dots P_{Z_n}(Z_n \in \mathcal{E}_n) \\ &= P_Z(Z_1 \in \mathcal{E}_1) \dots P_Z(Z_n \in \mathcal{E}_n) \end{aligned}$$

## Equivalently:

$$D = ((\vec{X}_1, Y_1), \dots, (\vec{X}_n, Y_n)) \in (\mathcal{X} \times \mathcal{Y})^n$$

where  $(\vec{X}_i, Y_i) \sim P_{\vec{X}, Y}$  are independent for all  $i \in \{1, \dots, n\}$   
↑ “sampled/distributed according to”

$D$  contains  $n$  independent samples of  $(\vec{X}_i, Y_i)$   
"feature-label" pairs all coming from the same  
distribution  $P_{\vec{X}, Y}$

## Functions of Random Variables

A function of a r.v. is a r.v.

Ex: ( $X$  is a fair six-sided dice)

$$X \in \{1, 2, 3, 4, 5, 6\} = \mathcal{X} \quad \text{with} \quad p(x) = \frac{1}{6}$$

$$f(X) = X^2 \in \underbrace{\{1^2, 2^2, 3^2, 4^2, 5^2, 6^2\}}_{\text{outcome space for } f(X)} = \mathcal{Y} \quad \text{is a r.v.}$$

$$\text{Notice } f: \mathcal{X} \rightarrow \mathcal{Y}$$

Sometimes we give the r.v. a new symbol

$$Y = f(X) = X^2$$

$$(\text{proof}) \quad P_Y(y) = P_{f(X)}(y) = \frac{1}{6} \quad \text{where } y \in \{1, 2^2, 3^2, 4^2, 5^2, 6^2\}$$

$$\text{In this case } p_Y(x^2) = p(x) \quad \text{where } x \in \mathcal{X}$$

$$\text{ex: } p_Y(9) = p_Y(3^2) = p(3) = \frac{1}{6}$$

Ex: ( $X$  is the payout from a slot machine)

$X \in [-10, 10]$  with  $p(x) = \frac{1}{20}$ ,  $P = \text{Uniform}(-10, 10)$

$Y = f(X) = X^2 \in [0, 100] = \mathcal{Y}$

$p_Y(y) = \frac{1}{20\sqrt{y}}$  much more complicated

In general  $p_Y$  is complicated and we will not need to know how to calculate it

The Predictor and Learner are functions of r.v.

Ex: (Predictor)

$\vec{X} = (X_1, X_2)^T \in \mathbb{R}^2 = \mathcal{X}$  with  $P_{\vec{X}}$

predictor:  $f: \mathcal{X} \Rightarrow \mathcal{Y}$  where  $\mathcal{Y} = \mathbb{R}$

$f(\vec{X}) = 3 + 6X_1 + 2.5X_2$  is a r.v. with values in  $\mathcal{Y}$   
and has some distribution  $P_{f(\vec{X})}$

Ex: (Learner)

$D = ((\vec{X}_1, Y_1), \dots, (\vec{X}_n, Y_n)) \in (\mathcal{X} \times \mathcal{Y})^n$  with  $P_D$



Learner:  $\mathcal{A}: (\mathcal{X} \times \mathcal{Y})^n \rightarrow \{f \mid f: \mathcal{X} \rightarrow \mathcal{Y}\} = \mathcal{F}$

$\mathcal{A}(D) = f$  is a r.v. with values in  $\mathcal{F}$

example and has some distribution  $P_{\mathcal{A}(D)}$

if  $D = ((7, 6), (12, 2.5))$  where  $n=2, \mathcal{X}=\mathbb{R}, \mathcal{Y}=\mathbb{R}$

then  $f_D$  can be  $f(x) = 2.5 + 6x$

This means we can talk about things like:

- What is the probability the Predictor  $f(\vec{X})$  outputs some value  $y$
- What is the probability the Learner  $\mathcal{A}(D)$  outputs some predictor  $f$

# Expectation and Variance

Expected Value of a r.v.: average value of the r.v. if you sample from its distribution infinitely many times.

The r.v. must take values in  $\mathbb{R}$ .

It is not always the value we expect to see most frequently (that is the mode)

$X \in \mathcal{X}$  is a r.v. with pmf or pdf  $p$

$$\mathbb{E}[X] \stackrel{\text{def}}{=} \begin{cases} \sum_{x \in \mathcal{X}} x p(x) & \text{if } X \text{ is discrete} \\ \int_{\mathcal{X}} x p(x) dx & \text{if } X \text{ is continuous} \end{cases}$$

Ex: (fair six-sided dice)

$X \in \{1, 2, 3, 4, 5, 6\} = \mathcal{X}$  and  $P = \text{Uniform}(n=6)$

thus  $p(x) = \frac{1}{6}$

$$\begin{aligned} \mathbb{E}[X] &= \sum_{x \in \mathcal{X}} x p(x) = 1 \cdot \frac{1}{6} + 2 \cdot \frac{1}{6} + 3 \cdot \frac{1}{6} + 4 \cdot \frac{1}{6} + 5 \cdot \frac{1}{6} + 6 \cdot \frac{1}{6} \\ &= 3.5 \end{aligned}$$

This is not an number you can roll on a dice!

$E_x$ : (Unfair coin)

$X \in \{0, 1\}$  and  $P = \text{Bernoulli}(\alpha)$

thus  $p(1) = \alpha, p(0) = 1 - \alpha$

$$E[X] = \sum_{x \in \mathcal{X}} x p(x) = 0 \cdot (1 - \alpha) + 1 \cdot \alpha = \alpha$$

This is not a result of a coin flip (unless  $\alpha = 1$  or  $\alpha = 0$ )

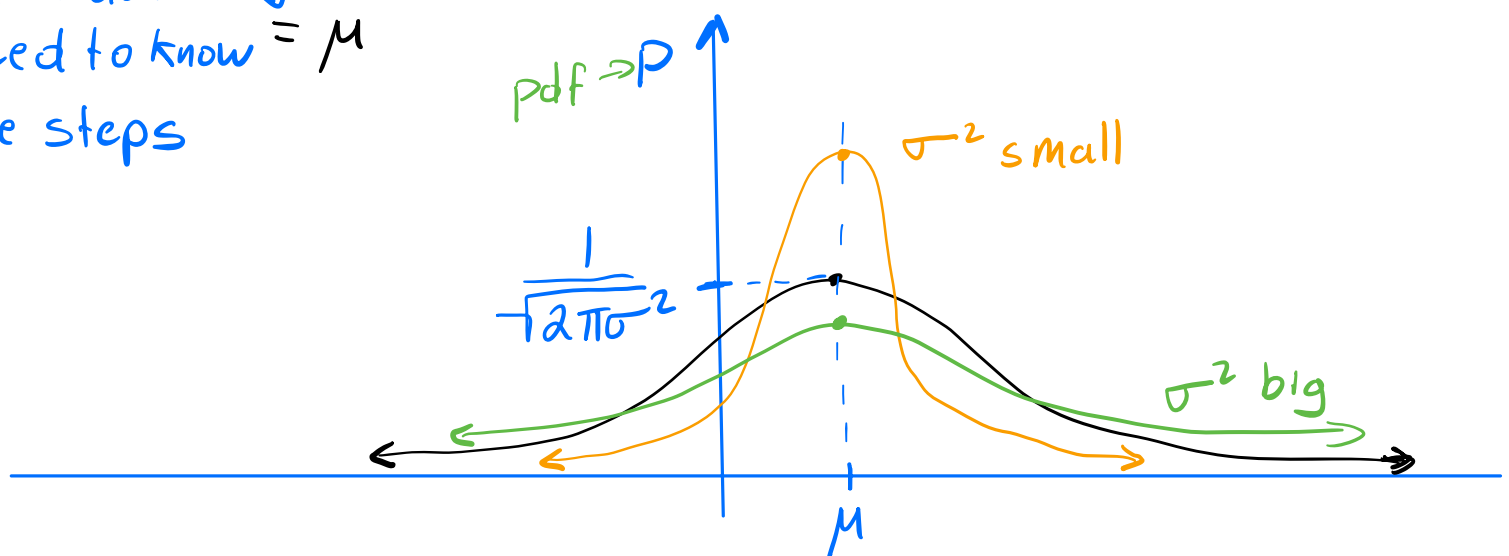
$E_x$ : (Normal distribution)

$X \in \mathbb{R} = \mathcal{X}$  and  $P = \mathcal{N}(\mu, \sigma^2)$

thus  $p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right)$

$$E[X] = \int_{\mathcal{X}} x \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right) dx$$

You don't need to know the steps  $= \mu$



## Expected value of functions of r.v.:

$X \in \mathcal{X}$  is a r.v. with pmf or pdf  $p$

The function  $f: \mathcal{X} \rightarrow \mathcal{Y}$  must have  $\mathcal{Y} = \mathbb{R}$

$$\mathbb{E}[f(X)] \stackrel{\text{def}}{=} \begin{cases} \sum_{x \in \mathcal{X}} f(x) p(x) & \text{if } X \text{ is discrete} \\ \int_{\mathcal{X}} f(x) p(x) dx & \text{if } X \text{ is continuous} \end{cases}$$

Ex: ( $X$  is the payout from a slot machine)

$X \in [-10, 10]$  with  $p(x) = \frac{1}{20}$ ,  $P = \text{Uniform}(-10, 10)$

$Y = f(X) = X^2 \in [0, 100] = \mathcal{Y}$

$p_Y(y) = \frac{1}{20\sqrt{y}}$  much more complicated

$$\mathbb{E}[f(X)] = \int_{\mathcal{X}} f(x) p(x) dx = \int_{-10}^{10} x^2 \frac{1}{20} dx$$

$$= \frac{x^3}{3} \cdot \frac{1}{20} \Big|_{-10}^{10}$$

$$= \left( \frac{1000}{3} - \left( \frac{-1000}{3} \right) \right) \cdot \frac{1}{20}$$

$$= \frac{2000}{60} = 33.333$$

It turns out

$$\begin{aligned}\mathbb{E}[f(x)] &= \mathbb{E}[Y] = \int_{\mathcal{Y}} y P_Y(y) dy \\ &= 33.333\end{aligned}$$

Usually we don't know  $P_Y = P_{f(x)}$

So we work with  $p$

Variance of a r.v.: How much the r.v. varies from its expected value on average

$X \in \mathcal{X}$  is a r.v. with pmf or pdf  $p$

$$\text{Var}[X] \stackrel{\text{def}}{=} \mathbb{E}\left[\underbrace{(X - \mathbb{E}[X])^2}_{\text{this is just a function of the r.v. } X}\right] = \mathbb{E}[X^2] - (\mathbb{E}[X])^2$$

this is just a function of the r.v.  $X$

Ex: (Unfair coin)

$X \in \{0, 1\}$  and  $P = \text{Bernoulli}(\alpha)$

thus  $p(1) = \alpha, p(0) = 1 - \alpha$

$$\begin{aligned} E[X] &= \sum_{x \in \mathcal{X}} x p(x) = 0 \cdot (1-\alpha) + 1 \cdot \alpha \\ &= \alpha \end{aligned}$$

$$\text{Var}[X] = E[(X - E[X])^2]$$

$$= \sum_{x \in \mathcal{X}} (x - E[X])^2 p(x)$$

$$= (0 - \alpha)^2 \cdot (1 - \alpha) + (1 - \alpha)^2 \cdot \alpha$$

$$= \alpha^2 - \alpha^3 + \alpha - 2\alpha^2 + \alpha^3$$

$$= \alpha - \alpha^2$$

$$= \alpha(1 - \alpha)$$

or  $\text{Var}[X] = E[X^2] - (E[X])^2$

$$= \sum_{x \in \mathcal{X}} x^2 p(x) - \alpha^2$$

$$= 0^2 \cdot (1 - \alpha) + 1^2 \cdot \alpha - \alpha^2$$

$$= \alpha(1 - \alpha)$$

$E_X$ : (Normal distribution)

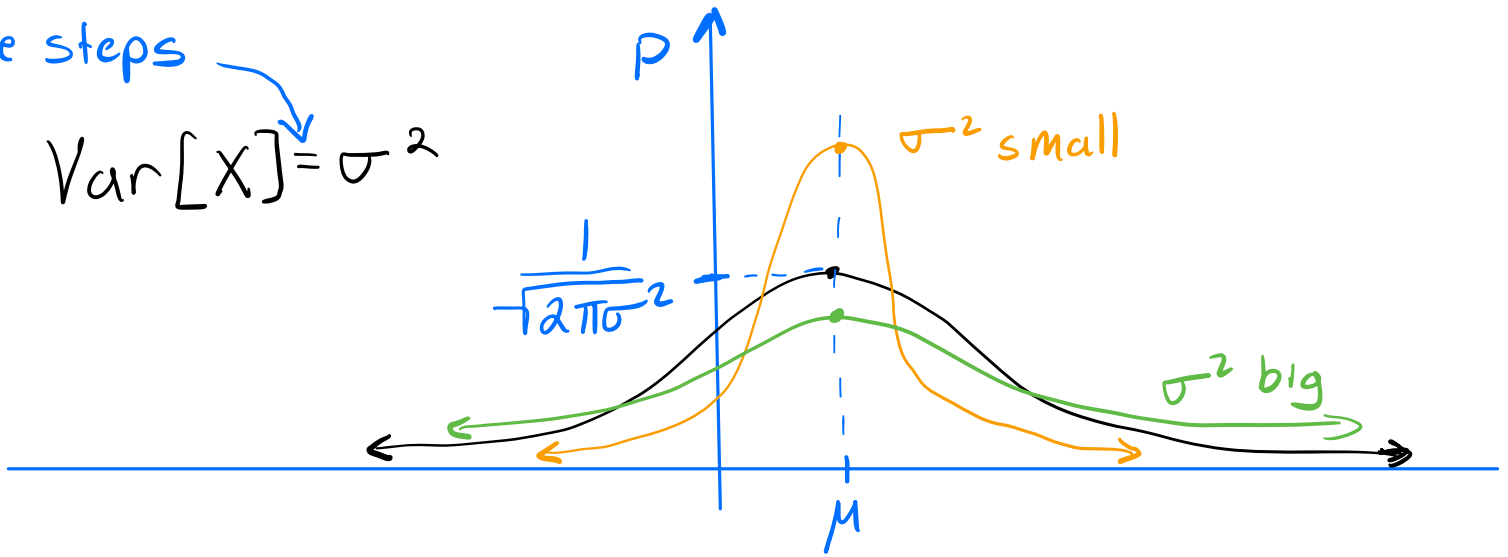
$$X \in \mathbb{R} = \mathcal{X} \quad \text{and} \quad P = \mathcal{N}(\mu, \sigma^2)$$

$$\text{thus} \quad p(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(x - \mu)^2\right)$$

$$E[X] = \int_{\mathcal{X}} x \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(x-\mu)^2\right) dx$$

You don't need to know the steps

$$\text{Var}[X] = \sigma^2$$



Multivariate Expected Value:

$Z = (X, Y) \in \mathcal{X} \times \mathcal{Y} = \mathcal{Z}$  is a r.v.

$$f: \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{R}$$

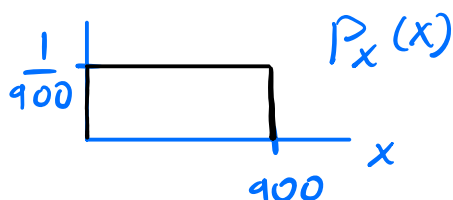
$$E[f(X, Y)] = \begin{cases} \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} f(x, y) p(x, y) & \text{if } X, Y \text{ are discrete} \\ \int_{\mathcal{X}} \int_{\mathcal{Y}} f(x, y) p(x, y) dy dx & \text{if } X, Y \text{ are continuous} \\ \int_{\mathcal{X}} \left( \sum_{y \in \mathcal{Y}} f(x, y) p(y|x) \right) p(x) dx & \text{if } Y \text{ is discrete and } X \text{ is continuous} \\ \sum_{x \in \mathcal{X}} \left( \int_{\mathcal{Y}} f(x, y) p(y|x) dy \right) p(x) & \text{if } Y \text{ is continuous and } X \text{ is discrete} \end{cases}$$

you can always use:

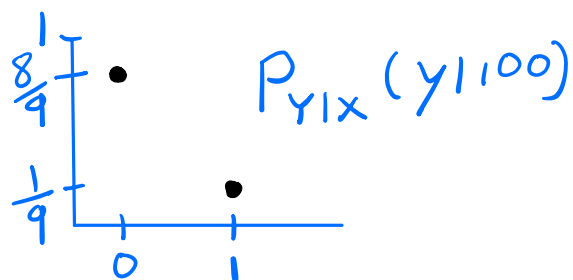
$$p(x, y) = p(y|x)p(x) = p(x|y)p(y)$$

$E_x$ :  $X \in \mathcal{X} = [0, 900]$ ,  $Y \in \mathcal{Y} = \{0, 1\}$   $\leftarrow$  Barolo

pdf:  $p_X = \text{Uniform}(0, 900)$   
 $= \frac{1}{900}$



$$p_{Y|X=x} = \text{Bernoulli}\left(\frac{x}{900}\right)$$



pmf:  $p_{Y|X}(y|x) = \begin{cases} \frac{x}{900} & \text{if } y=1 \\ 1 - \frac{x}{900} & \text{if } y=0 \end{cases}$   
 Defn of Bernoulli( $\frac{x}{900}$ )

$$f(x, y) = \left(\frac{x}{900} - y\right)^2$$

$$E[f(x, Y)] = \int_{\mathcal{X}} \left( \sum_{y \in \mathcal{Y}} f(x, y) p(y|x) \right) p(x) dx$$

$$= \int_0^{900} \left( \sum_{y \in \{0, 1\}} \left(\frac{x}{900} - y\right)^2 p(y|x) \right) p(x) dx$$

$$= \int_0^{900} \left( \left(\frac{x}{900} - 0\right)^2 \left(1 - \frac{x}{900}\right) + \left(\frac{x}{900} - 1\right)^2 \left(\frac{x}{900}\right) \right) \frac{1}{900} dx$$



$$= \frac{1}{900} \int_0^{900} \frac{x}{900} \left(1 - \frac{x}{900}\right) dx$$

$$= \frac{1}{900} \left( \frac{x^2}{1800} \Big|_0^{900} - \frac{x^3}{3 \cdot 900^2} \Big|_0^{900} \right)$$

$$= \frac{1}{6}$$

Conditional Expected Value:

$(X, Y) \in \mathcal{X} \times \mathcal{Y}$  is a r.v.

$P = P_{Y|X}$  is a conditional pmf or pdf

$f: \mathcal{Y} \rightarrow \mathbb{R}$

$$\mathbb{E}[f(Y) | X=x] = \begin{cases} \sum_{y \in \mathcal{Y}} f(y) p(y|x) & \text{if } Y \text{ is discrete} \\ \int_{\mathcal{Y}} f(y) p(y|x) & \text{if } Y \text{ is continuous} \end{cases}$$

## Useful Properties

Let  $X, Y$  be r.v. and  $c \in \mathbb{R}$  be a constant

$$1. \mathbb{E}[cX] = c \mathbb{E}[X]$$

$$2. \mathbb{E}[X+Y] = \mathbb{E}[X] + \mathbb{E}[Y]$$

$$3. \mathbb{E}[Y] = \mathbb{E}[\mathbb{E}[Y|X]]$$

$$4. \text{Var}[c] = 0$$

$$5. \text{Var}[cX] = c^2 \text{Var}[X]$$

will be on the  
formula sheet  
for midterms

If  $X$  and  $Y$  are independent:

$$6. \mathbb{E}[XY] = \mathbb{E}[X] \mathbb{E}[Y]$$

$$7. \text{Var}[X+Y] = \text{Var}[X] + \text{Var}[Y]$$