### **Section 7** CLT and Joint Distributions

# CONTENT REVIEW

# **this PDF is really messy :** $f_X(x) = \frac{1}{\sqrt{2\pi\sigma}}e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

use the <u>Phi Table</u> to easily look up the value of P(Z < z)

1. Find  $\mu$ )/ $\sigma^2$  of normal RV X

1. Standardize RV X~N( $\mu$ ,  $\sigma^2$ ) to get (X- $\mu$ )/ $\sigma^2$  ~ Z ~ N(0,1)

2. Use **Phi table** to get appropriate value with  $Z = (X-\mu)/\sigma^2$ 

3. Solve for X



### normal distribution

#### properties of the normal distribution

**Closure for Normal Distribution** 

Let X~N( $\mu$ ,  $\sigma^2$ ). Then aX + b~N(a $\mu$  + b, b<sup>2</sup> $\sigma^2$ )

"Reproductive" Property

Let X1,...,Xn be independent normal RVs with E[Xi]= $\mu$  and Var(Xi= $\sigma$ i

$$X = \sum_{i=1}^{n} (a_i X_i + b) \sim N\left(\sum_{i=1}^{n} (a_i \mu_i + b), \sum_{i=1}^{n} a_i^2 \sigma_i^2\right)$$

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### normal distribution



By symmetry of normal distribution, P(X < -k) = P(X > k)
Φ(a) = P(Z < a) where Z (standard normal) follows N(0, 1)</li>
Φ(-k) = P(Z < k) = P(Z>k) = 1-P(Z < k) = 1-Φ(k) <u>^ this is useful because negative values aren't on the table!</u> it turns out that a lot of data collected in real world experiments follow a normal distribution!

### central limit theorem

if  $X = X_1 + X_2 + ... + X_n$  are **iid** where  $E[Xi] = \mu$  and  $Var(Xi) = \sigma^2$ , X can be approximated by a <u>normal distribution</u>  $X \sim N(n\mu, n\sigma^2)$ as n becomes really large

this also means that as n increases, (X- $\mu$  /  $\sigma^{2}$ ) ~ Z ~ N(0,1)

if Xi is discrete random variables, use continuity correction because we'd be using a continuous distribution to approximate a discrete distribution

To estimate probability that discrete RV lands in (integer) interval {a,b} compute probability continuous approximation lands in interval [a-0.5, b+0.5] 1. set up the problem

(what do we want to solve for/what is the probability we want to be true?)

2. if the distribution is discrete, apply continuity correction here

central limit

theorem

2. apply CLT to X = Xi + ... + Xn

3. convert to standard normal

4. solve!

## joint distribution

shows the distribution for two (or more) random variables

 $p_{X,Y}(x, y) = P(X=x, Y=y)$ 

	Discrete	Continuous
Joint PMF/PDF	$p_{X,Y}(x,y) = \mathbb{P}\left(X = x, Y = y\right)$	$f_{X,Y}(x,y) \neq \mathbb{P}\left(X = x, Y = y\right)$
Joint range/support		
$\Omega_{X,Y}$	$\{(x,y)\in\Omega_X\times\Omega_Y:p_{X,Y}(x,y)>0\}$	$\{(x,y)\in\Omega_X\times\Omega_Y: f_{X,Y}(x,y)>0\}$
Joint CDF	$F_{X,Y}(x,y) = \sum_{t \leqslant x, s \leqslant y} p_{X,Y}(t,s)$	$F_{X,Y}(x,y) = \int_{-\infty}^{x} \int_{-\infty}^{y} f_{X,Y}(t,s)  ds dt$
Normalization	$\sum_{x,y} p_{X,Y}(x,y) = 1$	$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x,y)  dx dy = 1$
Marginal PMF/PDF	$p_X(x) = \sum_y p_{X,Y}(x,y)$	$f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dy$
Expectation	$\mathbb{E}[g(X,Y)] = \sum_{x,y} g(x,y) p_{X,Y}(x,y)$	$\mathbb{E}[g(X,Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x,y) f_{X,Y}(x,y) dx dy$
Independence	$\forall x, y, p_{X,Y}(x, y) = p_X(x)p_Y(y)$	$\forall x, y, f_{X,Y}(x, y) = f_X(x) f_Y(y)$
must have	$\Omega_{X,Y} = \Omega_X \times \Omega_Y$	$\Omega_{X,Y} = \Omega_X \times \Omega_Y$
Conditional PMF/PDF	$p_{X Y}(x y) = rac{p_{X,Y}(x,y)}{p_Y(y)}$	$f_{X Y}(x y) = \frac{f_{X,Y}(x,y)}{f_Y(y)}$
Conditional Expectation	$\mathbb{E}[X Y=y] = \sum_x x \cdot p_{X Y}(x y)$	$\mathbb{E}[X Y=y] = \int_{-\infty}^{\infty} x f_{X Y}(x y) dx$

X/Y	1	2	3
0	0	0.2	0.1
1	0.3	0	0.4

these are the values X takes on



these are the values Y takes on

these are the values X takes on



these are the values X takes on these are the values Y takes on

the values in the table show the joint probabilities - for example this highlighted value is P(X=1, Y-3)

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(a) Identify the range of X ( $\Omega_X$ ), the range of Y ( $\Omega_Y$ ), and their joint range ( $\Omega_{X,Y}$ ).

• Based on the table (specifically what's highlighted in yellow and pink), we know that the range of X is {0, 1}, and the range of Y is {1,2,3}

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- In this case, that would be the set of pairs:
  - $\Omega_{\chi,\gamma} = \{(0, 2), (0,3), (1,1), (1,3)\}$
- We <u>don't</u> include the pairs (0, 1) and (1,2) because the joint pmf is 0 for those pairs



- The marginal PMF for X is just like asking what the PMF for X is based on the joint PMF
- There are only two values in the range of X so we can try defining this PMF by looking at the probabilities for each value separately!
- First, we want to find P(X=0)



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- In general, the marginal pmf looks like:

$$p_X(x) = \sum_{y \in \Omega_Y} p_{X,Y}(x,y))$$

X/Y	1	2	3
0	0	0.2	0.1
1	0.3	0	0.4

(d) Are *X* and *Y* independent? Why or why not?

• If we want to prove that X and Y <u>are</u> independent, we would need to show <u>both</u> of the conditions to be true:

$$\forall x, y, p_{X,Y}(x, y) = p_X(x)p_Y(y)$$
$$\Omega_{X,Y} = \Omega_X \times \Omega_Y$$

• However, note that the second condition is not true in this case! (take a look at the ranges we found in part a). So, X and Y are not independent.

### Thanks for coming today!