# CSE 312 Foundations of Computing II

# **Lecture 17: The Normal Distribution**

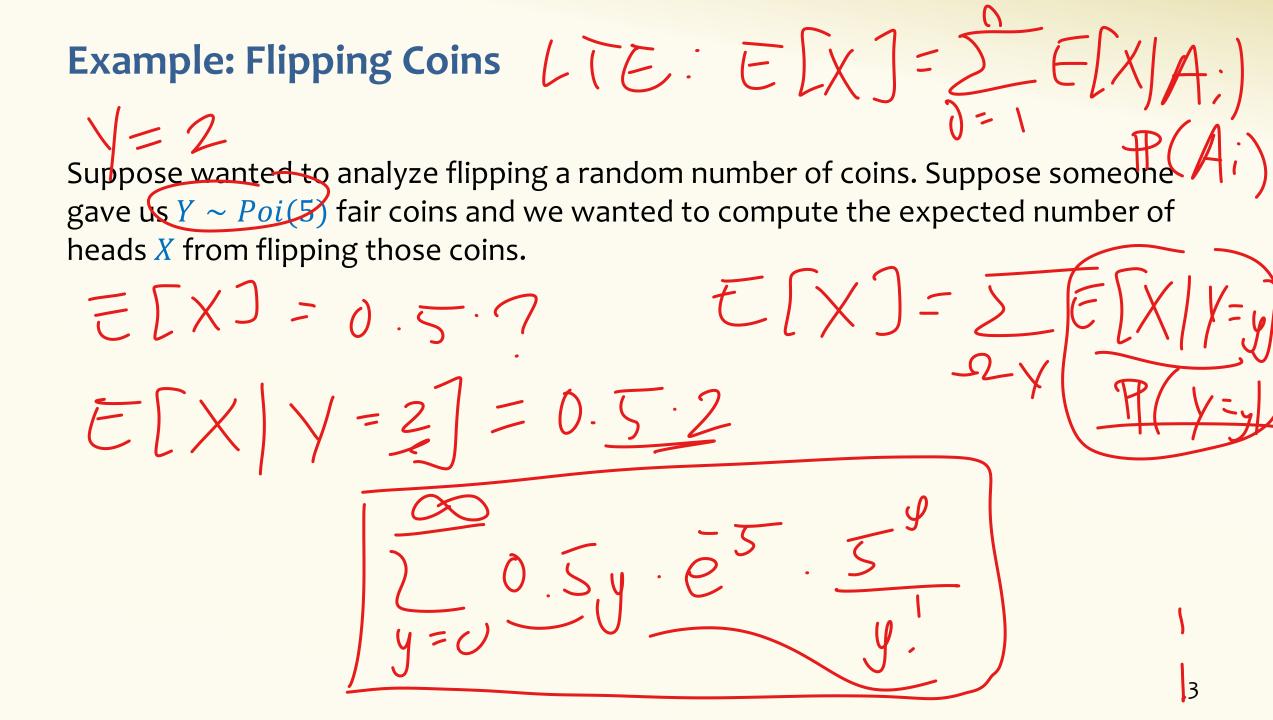


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Slide Credit: Based on Stefano Tessaro's slides for 312 9au incorporating ideas from Anna Karlin, Alex Tsun, Rachel Lin, Hunter Schafer & myself ©



- Law of Total Expectation (LTE) Practice
- Chebyshev's Inequality
- The Normal Distribution
- Practice with Normals



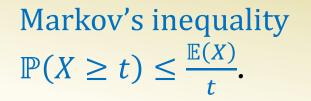
# Agenda

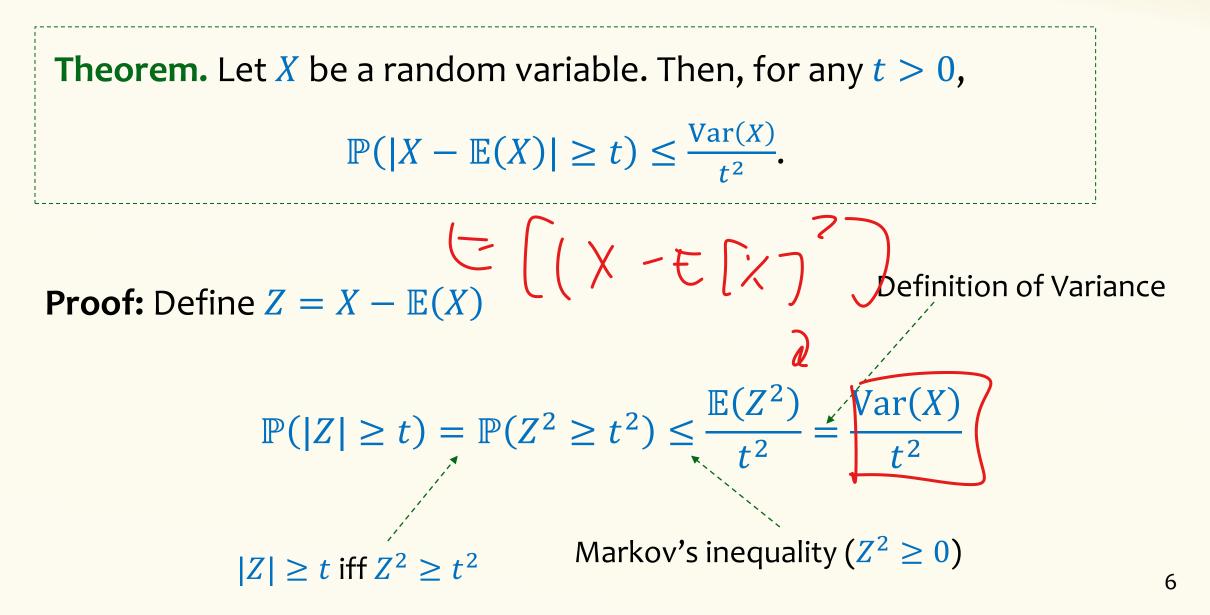
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# Using variance

• If we know more about the random variable, e.g. its variance, we can get a better bound!

# **Chebyshev's Inequality**





**Example – Binomial Random Variable**  $\mathbb{P}(|X - \mathbb{E}(X)| \ge t) \le \frac{\operatorname{Var}(X)}{t^2}.$ 

Let X be Binomial RV with parameters. n, p = 0.5p = 0p(1-p)Var(X) = $\mathbb{E}(X) = \frac{n}{2}$ What is the probability that  $X \ge \frac{3n}{4}$ ? Chebychev's inequality:  $\mathbb{P}\left(X \ge \frac{3n}{4}\right) \stackrel{\sim}{=} \mathbb{P}\left(X - \frac{n}{2} \ge \frac{n}{4}\right) \stackrel{\sim}{=} \mathbb{P}\left(X \ge \frac{3n}{4}\right) \stackrel{\sim}{=} \mathbb{P}\left(X - \frac{n}{2} \ge \frac{n}{4}\right) \stackrel{\sim}{=} \mathbb{P}\left(X \ge \frac{3n}{4}\right) \stackrel{\sim}{=} \mathbb$  $P(|X - \frac{1}{2}|2\frac{1}{2})$ Markov's inequality:  $\mathbb{P}\left(X \ge \frac{3n}{4}\right) \le \frac{4}{3n} \cdot \frac{n}{2} = \frac{2}{3}$ 

### **Tail Bounds**

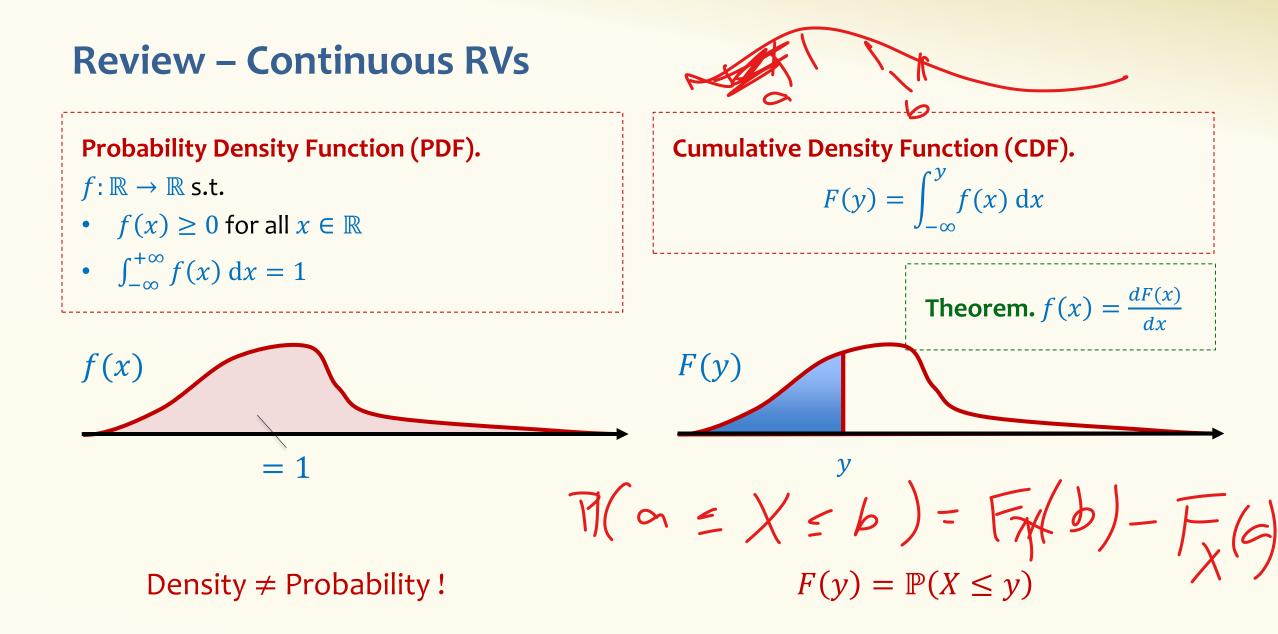
Useful for approximations of complex systems. How good the approximation is depends on the actual distribution and the context you are using it in.

 Usually loose upper-bounds are okay when designing for worstcase

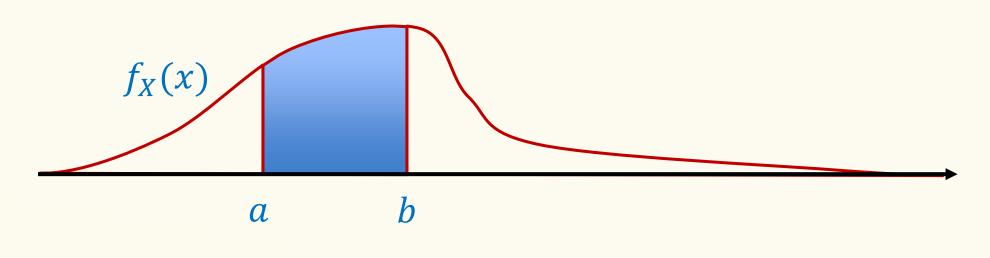
Generally, the more you know about your random variable the better tail bounds you can get.



- Law of Total Expectation (LTE) Practice
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### **Review – Continuous RVs**



$$\mathbb{P}(X \in [a,b]) = \int_a^b f_X(x) dx = F_X(b) - F_X(a)$$

### **Exponential Distribution**

**Definition.** An **exponential random variable** *X* with parameter  $\lambda \ge 0$  is follows the exponential density

$$f_X(x) = \begin{cases} \lambda e^{-\lambda x} & x \ge 0\\ 0 & x < 0 \end{cases}$$

We write  $X \sim \text{Exp}(\lambda)$  and say X that follows the exponential distribution.

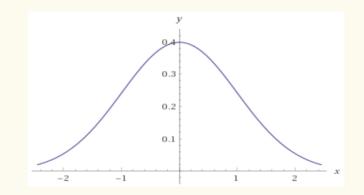
 $\lambda = 2^{-2}$   $\lambda = 1.5^{-1.5}$   $\lambda = 1^{-1}$   $\lambda = 0.5^{-0.5}$ 

### **The Normal Distribution**

**Definition.** A Gaussian (or normal) random variable with parameters  $\mu \in \mathbb{R}$  and  $\sigma \ge 0$  has density

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

(We say that X follows the Normal Distribution, and write  $X \sim \mathcal{N}(\mu, \sigma^2)$ )





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**Fact.** If 
$$X \sim \mathcal{N}(\mu, \sigma^2)$$
, then  $\mathbb{E}(X) = \mu$ , and  $Var(X) = \sigma^2$ 

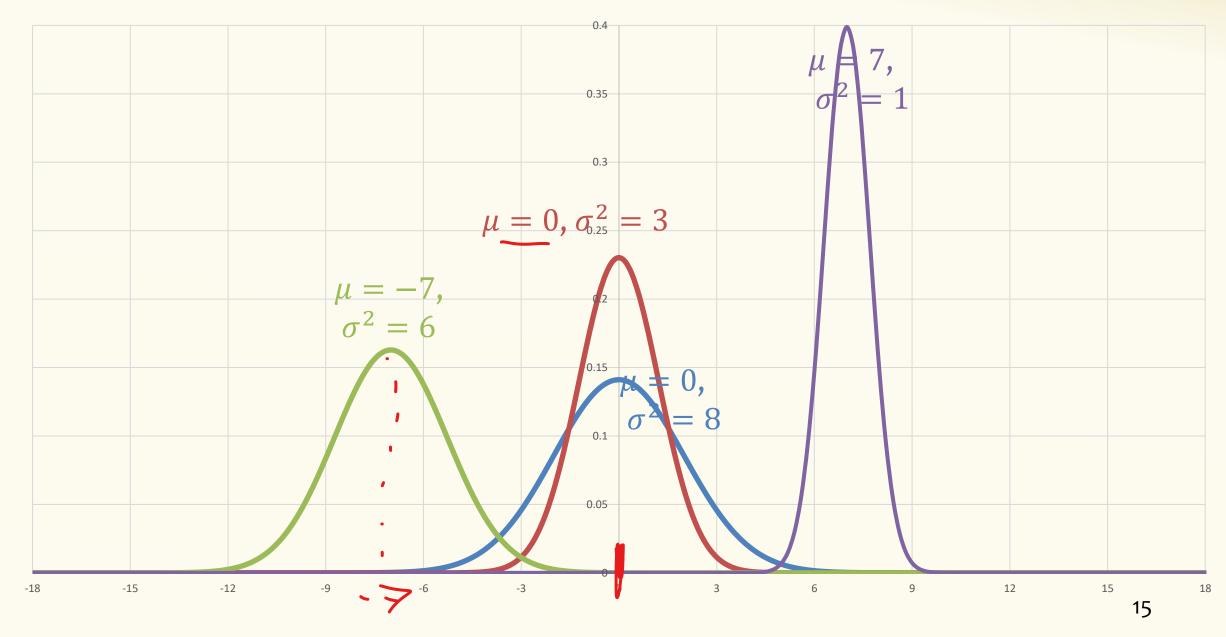
Expectation follows from density being symmetric around  $\mu$ ,  $f_X(\mu - x) = f_X(\mu + x)$ 



Gauss

### **The Normal Distribution**

#### Aka a "Bell Curve" (imprecise name)



# Shifting and Scaling – turning one normal dist into another

**Fact.** If 
$$X \sim \mathcal{N}(\mu, \sigma^2)$$
, then  $Y = aX + b \sim \mathcal{N}(a\mu + b, a^2\sigma^2)$ 

**Proof.**  $\mathbb{E}(Y) = a \mathbb{E}(X) + b = a\mu + b$   $Var(Y) = a^2 Var(X) = a^2 \sigma^2$ Can show with algebra that the PDF of Y = aX + b is still normal.

Note: 
$$\frac{X-\mu}{\sigma} \sim \mathcal{N}(0,1)$$

# **CDF of normal distribution**

**Fact.** If 
$$X \sim \mathcal{N}(\mu, \sigma^2)$$
, then  $Y = aX + b \sim \mathcal{N}(a\mu + b, a^2\sigma^2)$ 

Standard (unit) normal 
$$Z \sim \mathcal{N}(0, 1)$$

**CDF.** 
$$\Phi(z) = \mathbb{P}(Z \le z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{z} e^{-x^2/2} dx$$
 for  $Z \sim \mathcal{N}(0, 1)$ 

Note:  $\Phi(z)$  has no closed form – generally given via tables

$$\Phi(z) = P(Z \leq z)$$

### Table of $\Phi(z)$ CDF of Standard Normal Distn

Make sure to use the one linked on the site!

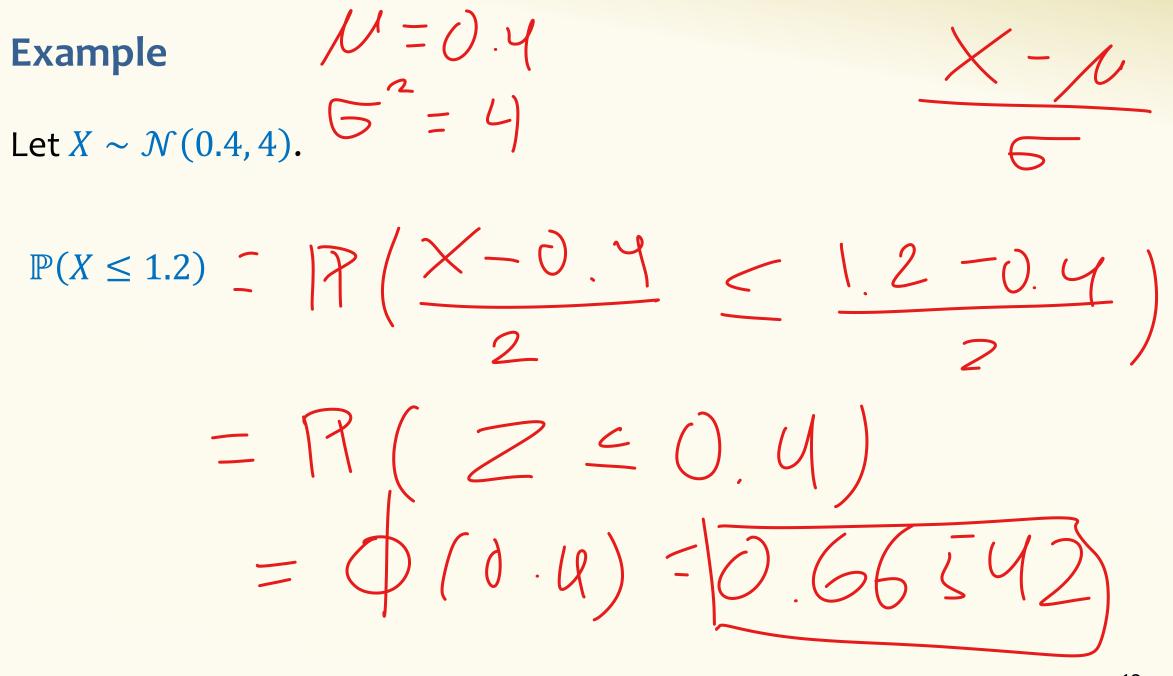
\_\_\_\_

Z

 $\Phi(z)$ 

PI(Z = 0.42)

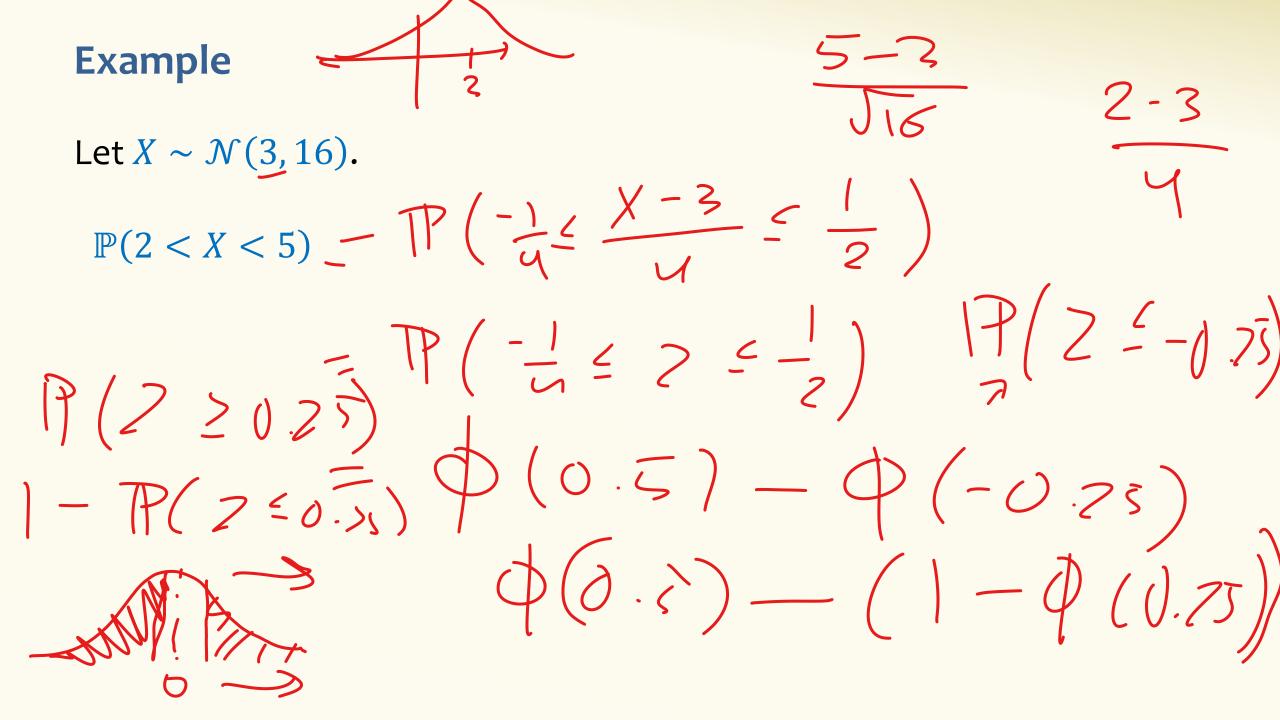
	Table: $\mathbb{P}(Z \leq z)$ when $Z \sim \mathcal{N}(0, 1)$											
	$\overline{z}$	0.90	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	
	0.0	0.5	0.50399	0.50798	0.51197	0.51595	0.51994	0.52392	0.5279	0.53188	0.53586	
	0.1	0.53983	0.5438	0.54776	0.55172	0.55567	0.55962	0.56356	0.56749	0.57142	0.57535	
	0.2	0.57926	0.58317	0.58706	0.59095	0.59483	0.59871	0.60257	0.60642	0.61026	0.61409	
	0.3	0.61791	0.62172	0.62552	0.6293	0.63307	0.63683	0.64058	0.64431	0.64803	0.65173	
	0.4	0.65542	0.6591	0.66276	0.6664	0.67003	0.67364	0.67724	0.68082	0.68439	0.68793	
	0.5	0.60146	0.69497	0.000 II	0.70194	0.7054	0.70884	0.71226	0.71566	0.71904	0.7224	
	0.6	0.72575	0.72907	0.73237	0.73565	0.73891	0.74215	0.74537	0.74857	0.75175	0.7549	
	0.7	0.75804	0.76115	0.76424	0.7673	0.77035	0.77337	0.77637	0.77935	0.7823	0.78524	
	0.8	0.78814	0.79103	0.79389	0.79673	0.79955	0.80234	0.80511	0.80785	0.81057	0.81327	
	0.9	0.81594	0.81859	0.82121	0.82381	0.82639	0.82894	0.83147	0.83398	0.83646	0.83891	
	1.0	0.84134	0.84375	0.84614	0.84849	0.85083	0.85314	0.85543	0.85769	0.85993	0.86214	
	1.1	0.86433	0.8665	0.86864	0.87076	0.87286	0.87493	0.87698	0.879	0.881	0.88298	
	1.2	0.88493	0.88686	0.88877	0.89065	0.89251	0.89435	0.89617	0.89796	0.89973	0.90147	
	1.3	0.9032	0.9049	0.90658	0.90824	0.90988	0.91149	0.91309	0.91466	0.91621	0.91774	
	1.4	0.91924	0.92073	0.9222	0.92364	0.92507	0.92647	0.92785	0.92922	0.93056	0.93189	
	1.5	0.93319	0.93448	0.93574	0.93699	0.93822	0.93943	0.94062	0.94179	0.94295	0.94408	
	1.6	0.9452	0.9463	0.94738	0.94845	0.9495	0.95053	0.95154	0.95254	0.95352	0.95449	
	1.7	0.95543	0.95637	0.95728	0.95818	0.95907	0.95994	0.9608	0.96164	0.96246	0.96327	
	1.8	0.96407	0.96485	0.96562	0.96638	0.96712	0.96784	0.96856	0.96926	0.96995	0.97062	
	1.9	0.97128	0.97193	0.97257	0.9732	0.97381	0.97441	0.975	0.97558	0.97615	0.9767	
	2.0	0.97725	0.97778	0.97831	0.97882	0.97932	0.97982	0.9803	0.98077	0.98124	0.98169	
	21	0.98214	0.98257	0.983	0.98341	0.98382	0.98422	0.98461	0.985	0.98537	0.98574	
C	2.2	0.9861	0.98645	0.98679	0.98713	0.98745	0.98778	0.98809	0.9884	0.9887	0.98899	
	2.3	0.98928	0.98956	0.98983	0.9901	0.99036	0.99061	0.99086	0.99111	0.99134	0.99158	
	2.4	0.9918	0.99202	0.99224	0.99245	0.99266	0.99286	0.99305	0.99324	0.99343	0.99361	
	2.5	0.99379	0.99396	0.99413	0.9943	0.99446	0.99461	0.99477	0.99492	0.99506	0.9952	
	2.6	0.99534	0.99547	0.9956	0.99573	0.99585	0.99598	0.99609	0.99621	0.99632	0.99643	
	2.7	0.99653	0.99664	0.99674	0.99683	0.99693	0.99702	0.99711	0.9972	0.99728	0.99736	
	2.8	0.99744	0.99752	0.9976	0.99767	0.99774	0.99781	0.99788	0.99795	0.99801	0.99807	
	2.9	0.99813	0.99819	0.99825	0.99831	0.99836	0.99841	0.99846	0.99851	0.99856	0.99861	
	3.0	0.99865	0.99869	0.99874	0.99878	0.99882	0.99886	0.99889	0.99893	0.99896	0.999	



# Example

Let  $X \sim \mathcal{N}(0.4, 4 = 2^2)$ .

$$\mathbb{P}(X \le 1.2) = \mathbb{P}\left(\frac{X - 0.4}{2} \le \frac{1.2 - 0.4}{2}\right)$$
$$= \mathbb{P}\left(\frac{X - 0.4}{2} \le 0.4\right) = \Phi(0.4) \approx 0.6554$$
$$\sim \mathcal{N}(0, 1)$$
$$\begin{array}{c} 0.1 & 0.5398 & 0.5438\\ 0.2 & 0.5793 & 0.5832\\ 0.3 & 0.6179 & 0.6217\\ 0.4 & 0.6554 & 0.6591\\ 0.5 & 0.6915 & 0.6950\\ 0.6 & 0.7257 & 0.7291\\ 0.7 & 0.7580 & 0.7611\end{array}$$



# Example

Let  $X \sim \mathcal{N}(3, 16)$ .

$$\mathbb{P}(2 < X < 5) = \mathbb{P}\left(\frac{2-3}{4} < \frac{X-3}{4} < \frac{5-3}{4}\right)$$
$$= \mathbb{P}\left(-\frac{1}{4} < Z < \frac{1}{2}\right)$$
$$= \Phi\left(\frac{1}{2}\right) - \Phi\left(-\frac{1}{4}\right)$$
$$= \Phi\left(\frac{1}{2}\right) - \left(1 - \Phi\left(\frac{1}{4}\right)\right) \approx 0.29017$$

# **Example – Off by Standard Deviations**

Let  $X \sim \mathcal{N}(\mu, \sigma^2)$ .

 $\mathbb{P}(|X - \mu| < k\sigma) =$ 

### **Example – Off by Standard Deviations**

Let  $X \sim \mathcal{N}(\mu, \sigma^2)$ .

$$\mathbb{P}(|X - \mu| < k\sigma) = \mathbb{P}\left(\frac{|X - \mu|}{\sigma} < k\right) =$$
$$= \mathbb{P}\left(-k < \frac{X - \mu}{\sigma} < k\right) = \Phi(k) - \Phi(-k)$$

e.g. *k* = 1:68%, *k* = 2:95%, *k* = 3:99%

Summary of procedure for doing calculations with normal r.v.

If 
$$X \sim \mathcal{N}(\mu, \sigma^2)$$
, then  $\frac{X - \mu}{\sigma} \sim \mathcal{N}(0, 1)$ 

Therefore,

$$F_X(z) = \mathbb{P}(X \le z) = \mathbb{P}\left(\frac{X-\mu}{\sigma} \le \frac{z-\mu}{\sigma}\right) = \Phi\left(\frac{z-\mu}{\sigma}\right)$$

### **CDF of normal distribution**

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If 
$$X \sim \mathcal{N}(\mu, \sigma^2)$$
, then  $F_X(z) = \mathbb{P}(X \le z) = \mathbb{P}\left(\frac{X-\mu}{\sigma} \le \frac{z-\mu}{\sigma}\right) = \Phi(\frac{z-\mu}{\sigma})$ 

# **Closure of the normal -- under addition**



**Fact.** If  $X \sim \mathcal{N}(\mu_X, \sigma_X^2)$ ,  $Y \sim \mathcal{N}(\mu_Y, \sigma_Y^2)$  (both independent normal RV) then  $aX + bY + c \sim \mathcal{N}(a\mu_X + b\mu_Y + c, a^2\sigma_X^2 + b^2\sigma_Y^2)$ 

Note: The special thing is that the sum of normal **RVs is still a normal RV.** 

The values of the expectation and variance is not surprising.

- Linearity of expectation (always true)
- When X and Y are independent,  $Var(aX + bY) = a^2 Var(X) + b^2 Var(Y)$