Probability of union: If $A_1, A_2, \ldots, A_n$ are *disjoint events* then $\Pr(A_1 \cup A_2 \cup \ldots \cup A_n) = \Pr(\bigcup_{i=1}^{n} A_i) = \Pr(A_1) + \Pr(A_2) + \ldots + \Pr(A_n) = \sum_{i=1}^{n} \Pr(A_i)$
If the events are not disjoint:
Two events A_1, A_2 : $\Pr(A_1 \cup A_2) = \Pr(A_1) + \Pr(A_2) - \Pr(A_1 \cap A_2)$
Three events: A_1, A_2, A_3 : $\Pr(A_1 \cup A_2 \cup A_3) = \Pr(A_1) + \Pr(A_2) + \Pr(A_3) - \Pr(A_1 \cap A_2) - \Pr(A_1 \cap A_3) - \Pr(A_2 \cap A_3) + \Pr(A_1 \cap A_2 \cap A_3)$

Conditional Probability: $\Pr(B|A) = \frac{\Pr(A \cap B)}{\Pr(A)}$ and $\Pr(A|B) = \frac{\Pr(A \cap B)}{\Pr(B)}$
$\Pr(A \cap B) = \Pr(B|A) \cdot \Pr(A)$ and
$\Pr(A \cap B) = \Pr(A|B) \cdot \Pr(B)$
In general: $\Pr(A_1 \cap A_2 \cap \ldots \cap A_n)$
$= \Pr(A_1) \cdot \Pr(A_2|A_1) \cdot \ldots \cdot \Pr(A_n|A_1 \cap A_2 \cap \ldots \cap A_{n-1})$

Independence: A, B are independent events if $\Pr(A|B) = \Pr(A)$ and $\Pr(B|A) = \Pr(B)$. Then:
$\Pr(A \cap B) = \Pr(A|B) \cdot \Pr(B) = \Pr(A) \cdot \Pr(B)$
$\Pr(A \cap B) = \Pr(B|A) \cdot \Pr(A) = \Pr(B) \cdot \Pr(A)$
In general if $A_1, A_2, \ldots, A_n$ are independent: $\Pr(A_1 \cap \ldots \cap A_n) = \Pr(A_1) \cdot \ldots \cdot \Pr(A_n)$. Note that if $A \cap B = \emptyset$ then the two events are *not independent*. Note that if A, B are independent then A, B^c are also independent.

Conditionally Independent: $A_1, A_2, \ldots, A_k$ are *conditionally independent* given B if, for every subset $A_{i_1}, \ldots, A_{i_m}$: $\Pr(A_{i_1} \cap \ldots \cap A_{i_m}|B) = \Pr(A_{i_1}|B) \cdot \ldots \cdot \Pr(A_{i_m}|B)$.

Bayes' Theorem: $\Pr(B_i|A) = \frac{\Pr(A|B_i) \cdot \Pr(B_i)}{\Pr(A)} = \frac{\Pr(A|B_i) \cdot \Pr(B_i)}{\sum_{j=1}^{k} \Pr(A|B_j) \cdot \Pr(B_j)}$

Uniform Distribution: $X = x, x \in \{1, 2, \ldots, k\}$ with all values x equally likely. The p.f. is $f_X(x) = \frac{1}{k}\{x|x = 1, 2, \ldots, k\}$

Binomial: n Bernoulli trials repeated independently with probability of success p.
$X :=$ number of success in n trials.
$x \in \{0, 1, \ldots, n\}$.
$f_X(x) = \Pr(X = x)$
$= \begin{cases} \binom{n}{x} p^x (1-p)^{n-x} & x = 0, \ldots, n \\ 0 & \text{o.w.} \end{cases}$
$\to X \sim \text{Bin}(n, p)$

Quantile Function: X continuous r.v. $F^{-1}(p)$ is the quantile function of X for $0 \leq p \leq 1. F^{-1}(p) = x \Rightarrow p = F(x)$.

Joint Continuous Distributions: Joint p.d.f. given by $f_{X,Y}(x, y) = \Pr((X, Y) \in A) = \iint f(x, y) dx dy$. To find the joint c.d.f. just integrate.

Negative-Binomial: Bernoulli trials until r successes are observed. $X :=$ number of failures $= \{0, 1, \ldots\}$. $p :=$ probability of success. $\Pr(X = x) = \Pr(x \text{ failures before } r \text{ successes}) = \Pr(x \text{ failures, } r-1 \text{ successes, } x+r-1 \text{ trials})) \cdot \Pr(\text{one success in last trial}) = \binom{x+r-1}{x}(1-p)^x p^r$.
$f_X(x) = \begin{cases} \binom{x+r-1}{x}(1-p)^x p^r & x = 0, 1, 2, \ldots \\ 0 & \text{o.w.} \end{cases}$

Hypergeometric: A box with A red balls and B blue balls. n balls are drawn *without replacement*. $X :=$ number of red balls $\leq \min(n, A)$. $\max(n - B, 0) \leq X \leq \min(n, A)$. Bounds: $\max(n - B, 0) \leq x \leq \min(n, A)$
$\to f_X(x) = \begin{cases} \frac{\binom{A}{x} \cdot \binom{B}{n-x}}{\binom{A+B}{n}} & \text{bounds} \\ 0 & \text{o.w.} \end{cases}$

Poisson: Counts occurences of an event. X is a Poisson r.v. with parameter λ (intensity) if the p.f. is $f_X(x) = \begin{cases} \frac{e^{-\lambda}\lambda^x}{x!} & x = 0, 1, 2, \ldots \\ 0 & \text{o.w.} \end{cases}$ with $\lambda > 0$.

Cumulative Distribution Function: (c.d.f.) For any r.v. X the c.d.f. is given by $F(x) = \Pr(X \leq x)$. Properties: If $x_1 < x_2 \Rightarrow \{X \leq x_1\} \subset \{X \leq x_2\}$ and so $\Pr(X \leq x_1) \leq \Pr(X \leq x_2) \Rightarrow F(x_1) \leq F(x_2)$
$\lim_{x \to -\infty} F(x) = 0$ and $\lim_{x \to \infty} F(x) = 1$
For a continuous r.v.:
$F(x) = \Pr(X \leq x) = \int_{-\infty}^{x} f(t) dt$
In general, $X \sim Unif[a, b] \Rightarrow$
$f(x) = \begin{cases} \frac{1}{b-a} & a \leq x \leq b \\ 0 & \text{o.w.} \end{cases}$.
$F(x) = \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a \leq x \leq b \\ 1 & x > b \end{cases}$

Marginal Distributions: In general for discrete r.v. $f_X(x) = \sum_y f(x, y)$ and $f_Y(y) = \sum_x f(x, y)$. In the case of 2 cont. r.v. $f_X(x) = \int_{-\infty}^{\infty} f(x, y) dy$ and $f_Y(y) = \int_{-\infty}^{\infty} f(x, y) dx$. $f_X(x)$ is the marginal p.d.f. of X. $f_Y(y)$ is the marginal p.d.f. of Y.

Independence: Two r.v. are independent if they produce independent events: $\Pr(X \in A, Y \in B) = \Pr(X \in A) \cdot \Pr(Y \in B)$. This implies: $\Pr(X \leq x, Y \leq y) = \Pr(X \leq x) \cdot \Pr(Y \leq y) \Rightarrow F(x, y) = F_X(x) \cdot F_Y(y)$.

Conditional Distributions: X, Y discrete r.v. with p.f. $f_X(x), f_Y(y)$ and joint p.f. $f(x, y)$. Then:
$\Pr(X = x|Y = y) = \frac{\Pr(X=x, Y=y)}{\Pr(Y=y)} = \frac{f(x,y)}{f_Y(y)}$.
$g_X(x|y) = \begin{cases} \frac{f(x,y)}{f_Y(y)} & \forall x, y : f_Y(y) > 0 \\ 0 & \text{o.w.} \end{cases}$
$\sum_x f_X(x|y) = \sum_x \frac{f(x,y)}{f_Y(y)} = \frac{1}{f_Y(y)} \cdot \sum_x f(x, y) = \frac{f_Y(y)}{f_Y(y)} = 1$.
In the continuous case X, Y with joint p.d.f. $f(x, y)$ and marginal p.d.f.'s $f_X(x)$ and $f_Y(y)$:
$g_X(x|y) = \begin{cases} \frac{f(x,y)}{f_Y(y)} & f_Y(y) > 0 \\ 0 & \text{o.w.} \end{cases}$
$\int_{-\infty}^{\infty} g_X(x|y) dx = \int_{-\infty}^{\infty} \frac{f(x,y)}{f_Y(y)} dx = \frac{1}{f_Y(y)} \int_{-\infty}^{\infty} f(x, y) dx = \frac{1}{f_Y(y)} \cdot f_Y(y) = 1$

Multivariate Distributions: $X_1, X_2, \ldots, X_n$ have a joint discrete distribution if $(X, \ldots, X_n)$ can have only a countable sequence of values in $\mathcal{R}^n$. The joint p.f. is $f(x_1, \ldots, x_n) = \Pr(X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n)$. $X_1, X_2, \ldots, X_n$ have a joint continuous distribution if there exists f such that $f((X_1, \ldots, X_n) \in \mathcal{C}) = \int_{\mathcal{C}} \cdots \int f(x_1, \ldots, x_n) dx_1 \ldots dx_n$. Here $f(x_1, \ldots, x_n)$ is the joint p.d.f. and $f(x_1, \ldots, x_n) = \frac{d^n F(x_1, \ldots, x_n)}{dx_1 \ldots dx_2}$. $F(x_1, \ldots, x_n) = \Pr(X_1 \leq x_1, X_2 \leq x_2, \ldots, X_n \leq x_n)$.

Marginal Distributions: $X_1, \ldots, X_n$ are cont. r.v. with joint p.d.f. $f(x_1, \ldots, x_n)$. Then the marginal distribution of $X_1 = f_{X_1}(x_1) = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} f(x_1, x_2, \ldots, x_n) dx_2 dx_3 \ldots dx_n$.
$F(x_1)$ is the marginal c.d.f. of X_1 and $F(x_1) = \Pr(X_1 \leq x_1) = \Pr(X_1 \leq x_1, X_2 < \infty, \ldots, X_n < \infty)$.

Bernoulli: An event A happens with probability p: $f_X(x) = p$ if $x = 1, (1-p)$ if $x = 0$

Geometric: Negative binomial with $r = 1$
$f_X(x) = \begin{cases} (1-p)^x p & x = 0, 1, \ldots \\ 0 & \text{o.w.} \end{cases}$

Conditional Distribution: $f(x_1, \ldots, x_n)$: joint p.d.f. of $x_1, \ldots, x_n$; $f_0(x_1, \ldots, x_k)$: joint p.d.f. of $x_1, \ldots, x_k$ with $k < n$. Then $\forall x_1, \ldots, x_k$ such that $f_0(x_1, \ldots, x_k) > 0$ the conditional p.d.f. of $X_{k+1}, \ldots, X_n$ given $X_1 = x_1, \ldots, X_k = x_k$ is $g(x_{k+1}, \ldots, x_n|x_1, \ldots, x_k) = \frac{f(x_1, \ldots, x_n)}{f_0(x_1, \ldots, x_k)}$.

Functions of one R.V: Consider a r.v. X cont. with p.d.f. $f_X(x)$. Assume we are interested in $Y = r(X)$ with r a function. What is the dist. of Y? Let $G_Y(y) = \Pr(Y \leq y)$ be the c.d.f. of Y: $G_Y(y) = \Pr(Y \leq y) = \Pr(r(X) \leq y) = \int f(x) dx \{x : r(x) \leq y\}$. To get the p.d.f. of Y take derivatives: $g_Y(y) = \frac{dG_Y(y)}{dy} = \frac{1}{2} y^{-\frac{1}{2}}$. For continuous r.v. such that $Y = r(X)$ with r differentiable and one-to-one: $g_Y(y) = f_X(r^{-1}(y)) \left| \frac{d}{dy} r^{-1}(y) \right|$.

Functions of two or more R.V.s: Discrete case: $X_1, X_2, \ldots, X_n$ r.v. with joint p.f. $f(x_1, \ldots, x_n$: $Y_1 = r_1(X_1, \ldots, X_n) \ldots Y_m = r_m(X_1, \ldots, X_n)$. Let $A := \{(x_1, \ldots, x_n)$:= such that $y_1 = r(x_1, \ldots, x_n) \ldots y_m = r(x_1, \ldots, x_n)\}$. Then: $g(y_1, \ldots, y_m) = \Pr(Y_1 = y_1, \ldots, Y_m = y_m) = \sum_{(x_1, \ldots, x_n) \in A} f(x_1, \ldots, x_n)$.
Continuous case: $X_1, X_2, \ldots, X_n$ cont. r.v. with joint p.d.f. $f(x_1, \ldots, x_n)$. Let $Y = r(X_1, \ldots, X_n) \to A_y = \{(x_1, \ldots, x_n)$ s.t. $r(x_1, \ldots, x_n) \leq y\}$ Then the c.d.f. of Y is $G(y) = \Pr(Y \leq y) = \Pr(r(X_1, \ldots, X_n) \leq y) = \int_{A_y} \ldots \int f(x_1, \ldots, x_n) dx_1 dx_2 \ldots dx_n$. The density/p.d.f. of Y is $g(y) = \frac{dG(y)}{dy}$.
If $Y = a_1 X_1 + a_2 X_2 + b \Rightarrow g(y) = \int_{-\infty}^{\infty} f\left(\frac{y - a_2 x_2 - b}{a_1}, x_2\right) \left|\frac{1}{a_1}\right| dx_2$

Permutations: Given an array of n elements: $n \cdot (n-1) \cdot (n-2) \cdot \ldots \cdot 1 = n!$
$P_{n,k} = \frac{n!}{(n-k)!}$, $P_{n,n} = n!$

Combinations: In general we can "combine" n elements taking k at a time in
$C_{n,k} = \frac{P_{n,k}}{k!} = \frac{n!}{(n-k)!k!} = \binom{n}{k}$.

Multinomial Coefficients: n elements into $k(k \geq 2)$ groups s.t. group j gets n_j elements and $\sum_{j=1}^{k} n_j = n$. The n_1 elements in the first group can be selected in $\binom{n}{n_1}$, the second in $\binom{n-n_1}{n_2}$, the third in $\binom{n-n_1-n_2}{n_3}$ and so on for the k groups. Then: $\binom{n}{n_1} \cdot \binom{n-n_1}{n_2} \cdot \binom{n-n_1-n_2}{n_3} \cdot \ldots \cdot \binom{n_k}{n_k} = \binom{n}{n_1, n_2, \ldots, n_k}$

Transformations: $X_1, \ldots, X_n$ cont. r.v.'s with joint pdf $f(x_1, \ldots, x_n)$. Let $Y_1 = r_1(X_1, \ldots, X_n), \ldots, Y_n = r_n(X_1, \ldots, X_n)$. To find the joint pdf of $Y_1, \ldots, Y_2$ for a one-to-one differentiable transformation $x_1 = s_1(y_1, \ldots, y_n), \ldots, x_n = s_n(y_1, \ldots, y_n) \rightarrow$ The joint pdf of $Y_1, \ldots, Y_n$ is $g(y_1, \ldots, y_n) = f(s_1, \ldots, s_n)\,|J|$ where

$$J = \det \begin{bmatrix} \frac{ds_1}{dy_1} & \cdots & \frac{ds_1}{dy_n} \\ \vdots & \ddots & \vdots \\ \frac{ds_n}{dy_1} & \cdots & \frac{ds_n}{dy_n} \end{bmatrix}$$

Linear Transformations: Suppose that $\vec{X} = \begin{pmatrix} X_1 \\ \vdots \\ X_n \end{pmatrix}$ and $\vec{Y} = \begin{pmatrix} Y_1 \\ \vdots \\ Y_n \end{pmatrix} = A\vec{X}$ (with A a non-singular matrix). Then $\vec{X} = A^{-1}\vec{Y}$ and $g_Y(y) = f_X(A^{-1}) \cdot \frac{1}{|\det A|}$

Markov Chains: A sequence of r.v.'s $X_1, X_2, \ldots$ is a stochastic process with discrete time parameter. X_1 is the initial state and X_n is the state at time n. A stochastic process with discrete time parameter is a Markov chain if for each n, $\Pr(X_{n+1} \leq b | X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n) = \Pr(X_{n+1} = \leq b | X_n = x_n)$. A Markov Chain is finite if there are finite possible states. Then: $\Pr(X_1 = x_1, \ldots, X_n = x_n) = \Pr(X_1 = x_1)\Pr(X_2 = x_2 | X_1 = x_1) \ldots \Pr(X_n = x_n | X_{n-1} = x_{n-1})$. Transition distributions: When a MC has k possible states then it has a transition distribution where there exist probabilities p_{ij} for $i, j = 1, \ldots, k$ such that $\forall n : \Pr(X_{n+1} = j | X_n = i) = p_{ij}$ and if $\Pr(X_{n+1} = j | X_n = i) = p_{ij} \forall n$ then it is a stationary transition distribution. In this case there is a matrix s.t.

$$\sum_{j=1}^{k} p_{ij} = 1, \forall i\text{: } P = \begin{bmatrix} p_{11} & \cdots & p_{1k} \\ \vdots & \ddots & \vdots \\ p_{k1} & \cdots & p_{kk} \end{bmatrix}$$

Transition of several steps: $P^m = P \cdot \ldots \cdot P$ Just exponentiate P and then find the resulting p_{ij}.

Expectation:
$E(X) = \int_{-\infty}^{\infty} x f(x) dx$ or $\sum_x x f(x)$

If $Y = r(X)$ and $f(x)$ is the p.d.f. of X : $E(Y) = \int_{-\infty}^{\infty} r(x) f(x) dx$
$Y = aX + b \rightarrow E(Y) = aE(X) + b$
a constant s.t. $\Pr(X \geq a) = 1$ then $E(X) \geq a$
b constant s.t. $\Pr(X \leq b) = 1$ then $E(X) \leq b$.
If $X_1, \ldots, X_n$ are r.v. then $E(X_1 + \ldots + X_n) = E(X_1) + \ldots + E(X_n)$
$E\left(\sum_{i=1}^{n} X_i\right) = \sum_{i=1}^{n} (E(X_i))$
$X_1, \ldots, X_n$ independent r.v.'s with finite expectation: $E\left(\Pi_{i=1}^{n} X_i\right) = \Pi_{i=1}^{n} (E(X_i))$
Bernoulli(p): $E(X) = p$
Binomial(n, p): $E(X) = np$
Poisson: $E(X) = \lambda$
Geometric: $E(X) = \frac{1-p}{p}$
Negative Binomial: $E(X) = \frac{r(1-p)}{p}$
Hypergeometric: $E(X) = \frac{nA}{A+B}$

Variance:
$V(X) = E[(X - \mu)^x]$ with $\mu = E(X)$
S.D.: $\sigma = \sqrt{V(X)}$
$V(X) \geq 0$!!!
X discrete: $V(X) = \sum_X (x - \mu)^2 f(x)$
X cont.: $V(X) = \int_{-\infty}^{\infty} (x - \mu)^2 f(x) dx$
$V(X) = E[(X - \mu)^2] = E(X^2) - \mu^2$
$V(X) = 0 \iff \Pr(X = c) = 1$
a, b constant: $V(aX + b) = a^2 V(X)$
$X_1, \ldots, X_n$ independent: $V(X_1 + \ldots + X_n) = V(X_1) + \ldots + V(X_n)$
Bernoulli: $V(X) = p(1 - p)$
Binomial: $V(X) = np(1 - p)$
Poisson: $V(X) = \lambda$
Geometric: $V(X) = \frac{1-p}{p^2}$
Negative Binomial: $V(X) = \frac{r(1-p)}{p^2}$
Hypergeometric: $V(X) = \frac{nAB}{(A+B)^2} \cdot \frac{A+B-n}{A+B-1}$

Conditional Variance:
$V(Y|X = x) = E(Y^2|X = x) - [E(Y|X = x)]^2$
$E(Y^2|X = x) = \int_{-\infty}^{\infty} y^2 g(y|x) dy$

Covariance:
$\text{Cov}(X, Y) = E[(X - \mu_X)(Y - \mu_Y)] = E(XY) - \mu_X \mu_Y \mu_Z$
Discrete: $E(XY) = \sum_x \sum_y xyf(x, y)$
Discrete: $\mu_X = E(X) = \sum_x \sum_y xf(x, y)$
Discrete: $\mu_Y = E(Y) = \sum_x \sum_y yf(x, y)$
Cont: $E(XY) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xyf(x, y) dx dy$
If X and Y are independent: $\text{Cov}(X, Y) = 0$

Correlation:
$\text{Corr}(X, Y) = \rho(X, Y)$
$= \frac{\text{Cov}(X,Y)}{\sqrt{V(X)}\sqrt{V(Y)}} = \frac{\text{Cov}(X,Y)}{\sigma_X \sigma_Y}$
Schwarz Ineq: $[E(UV)]^2 \leq E(U^2)E(V^2)$
$[\text{Cov}(X, Y)]^2 \leq V(X) \cdot V(Y)$
$-1 \leq \rho(X, Y) \leq 1$
Indep: $\text{Cov}(X, Y) = 0$ and $\rho(X, Y) = 0$
X r.v. w/ finite variance and $Y = aX + b$ s.t. $a \neq 0, a, b$, constant, then
$a > 0 \rightarrow \rho(X, Y) = 1$ and
$a < 0 \rightarrow \rho(X, Y) = -1$
X, Y w/ finite var. then $V(X+Y) = V(X) + V(Y) + 2 \cdot \text{Cov}(X, Y)$
$V(aX + bY) = a^2 V(X) + b^2 V(Y) + 2ab \cdot \text{Cov}(X, Y)$

Conditional Expectation:
Def: $E(Y|X = x)$
Cont: $= \int_{-\infty}^{\infty} y g_Y(y|x) dy$
Disc: $= \sum_y y g_Y(y|x)$
$E(Y|X = x)$ is a function of x not y
$h(x) = E(Y|x)$: $h(x)$ is not a random variable
$E(Y|X) \neq E(Y|X = x)$
$E(Y|X) = h(X) \rightarrow h(X)$ is a r.v.
$E(Y|X = x) = h(x) \rightarrow h(X)$ is not a r.v.
$E(E(Y|X)) = E(Y)$

Standard Normal Distribution:
X has standard normal dist. with $\mu = 0$ and $V = 0$, $X \sim N(0, 1)$ if:
p.d.f.: $\phi(x) = \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-x^2}{2}\right)$
c.d.f.: $\Phi(x) = \Pr(X \leq x)$
$= \int_{-\infty}^{x} \phi(u) du = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-u^2}{2}\right) du$
$\phi(x) = \phi(-x)$
$\Phi(x) = \Pr(X \leq x) = 1 - \Phi(-x)$
$\Phi^{-1}(p) = -\Phi(1 - p)$
$X \sim N(\mu, \sigma^2) \rightarrow Z = \frac{X-\mu}{\sigma}$
Then: $Z \sim N(0, 1)$ and cdf of X is
$F(x) = \Pr(X \leq x) = \Phi(\frac{x-\mu}{\sigma})$
Also: $F^{-1}(p) = \mu + \sigma\Phi^{-1}(p)$
Linear combo of r.v. $X_1, \ldots, X_n$ with $X_i \sim N(\mu_i, \sigma_i^2)$ then:
$\sum_{i=1}^{n} X_i = X_1 + \ldots + X_n \sim N(\sum_{i=1}^{n} \mu_i, \sum_{i=1}^{n} \sigma_i^2)$
Generally: $\sum_{i=1}^{n} a_i X_i = N(\sum_{i=1}^{n} a_i \mu_i, \sum_{i=1}^{n} a_i^2 \sigma_i^2)$
Linear combo of r.v.'s: $E(\bar{X_n}) = \mu$
$V(\bar{X_n}) = \frac{\sigma^2}{n}$
If Y is a linear combo of r.v.'s: $Y \sim N(\mu, \sigma^2)$
To find $\Pr(a < Y < b)$, use $Z = \frac{Y-\mu}{\sigma}$
$\Rightarrow Z \sim N(0, 1)$
Markov Inequality: X r.v., $\Pr(X \geq 0) = 1$, then: $\forall t > 0 : \Pr(X \geq t) \leq \frac{E(X)}{t}$
Chebyshev's Inequality: X r.v. w/ $V(X) \Rightarrow$ $\forall t > 0 : \Pr(|X - E(X)| \geq t) \leq \frac{V(X)}{t^2}$
So for $\bar{X_n} : \Pr(|\bar{X_n} - \mu| \geq t) \leq \frac{V(\bar{X_n})}{t^2} = \frac{\sigma^2}{nt^2}$

Central Limit Theorem:
$X_1, \ldots, X_n$ i.i.d. sample from distribution with mean μ and variance σ^2. For each $x(-\infty < x < \infty)$:
$\Rightarrow \lim_{n \to \infty} \Pr\left(\frac{\bar{X_n} - \mu}{\frac{\sigma}{\sqrt{n}}} \leq x\right) = \Phi(x)$
with $\Phi(x) =$ the c.d.f. of a standard normal

Min/Max: $X_1, \ldots, X_n$ independent r.v.'s. $Y_1 = \min(X_i)$, $Y_n = \max(X_i)$.
$F(x) = \Pr(X_i \leq x) = F(y) \cdot \ldots \cdot F(y) = [F(y)]^n$
$G_n(y) = \Pr(\max\{X_i\} \leq y) = [F(y)]^n \Rightarrow$
$g_n(y) = \frac{d}{dy} G_n(y) = n\,[F(y)]^{n-1} \left(\frac{dF(y)}{dy}\right) \Rightarrow$
$g_n(y) = n\,[F(y)]^{n-1} f(y)$. And:
$G_1(y) = Pr(\min\{X_i\} \leq y) = 1 - \Pr(\min\{X_i\} > y) = 1 - \Pr(X_i > y) = 1 - [(1 - \Pr(X_i \leq y))] = 1 - [(1 - F(y)) \cdot \ldots \cdot (1 - F(y))] = 1 - (1 - F(y))^n$
$\Rightarrow G_1(y) = 1 - (1 - F(y))^n$
$\Rightarrow g_1(y) = \frac{d}{dy} G_1(y) = n\,[1 - F(y)]^{n-1} (f(y))$

Other Stuff:
$\sum_{i=1}^{n} i = \frac{n(n+1)}{2}$, $\sum_{i=1}^{n} i^2 = \frac{n(n+1)(2n+1)}{6}$
$\sum_{i=0}^{n} c^i = \frac{c^{n+1}-1}{c-1}, c \neq 1; \sum_{i=0}^{\infty} c^i = \frac{1}{1-c}$
$\frac{d}{dx}(a^x) = \ln a$
$(fg)' = f'g + fg'$
$\left(\frac{f}{g}\right)' = \frac{f'g - fg'}{g^2}$
$\frac{d}{dx}(f(g(x))) = f'(g(x))g'(x)$
$\frac{d}{dx}(e^{g(x)}) = g'(x)e^{g(x)}$
$\frac{d}{dx}(\ln g(x)) = \frac{g'(x)}{g(x)}$
$\int \frac{1}{x} dx = \ln|x| + c$, $\int \frac{1}{ax+b} dx = \frac{1}{a} \ln|ax+b| + c$
$\int e^u du = e^u + c$, $\int a^u du = \frac{a^u}{\ln a} + c$
$\int_a^b f(g(x))g'(x) dx \Rightarrow u = g(x) \Rightarrow \int_{g(a)}^{g(b)} f(u) du$
$\int u dv = uv - \int v du$