Sets

Set Identities

Union: $A \cup B : \{x\epsilon\mathbb{S} : x\epsilon A \text{ OR } x\epsilon B\}$
Intersection: $A \cap B : \{x\epsilon\mathbb{S} : x\epsilon A \text{ AND } x\epsilon B\}$
Complement: $A^c : \{x\epsilon\mathbb{S} : x\not\epsilon A\}$
Difference: $A - B : \{x\epsilon\mathbb{S} : x\epsilon A, x\not\epsilon B\}$
Infinite Union: $\bigcup_{i=1}^{\infty} A_i : \{x\epsilon\mathbb{S}, x\epsilon A_i \ni A_i\}$
Infinite Intersection: $\bigcap_{i=1}^{\infty} A_i : \{x\epsilon\mathbb{S}, x\epsilon A_i \forall A_i\}$

Set Relationships

Containment: $A \subseteq B$ (A is a subset of B): $x\epsilon A$ means $x\epsilon B$
Equality: Two sets are equal if they contain each other: $A = B \therefore A \subseteq B, B \subseteq A$
Disjoint: $A \cap B = \{\}$

Set Properties

Commutativity: $A \cup B = B \cup A$, $A \cap B = B \cap A$
Associativity: $A \cup (B \cup C) = (A \cup B) \cup C$, $A \cap (B \cap C) = (A \cap B) \cap C$
Distributive: $A \cap (B \cup C) = (A \cap B) \cup (A \cap C)$, $A \cup (B \cap C) = (A \cup B) \cap (A \cup C)$
DeMorgan's Law: $(A \cup B)^c = A^c \cap B^c$, $(A \cap B)^c = A^c \cup B^c$

Sigma Algebras

Identity

A collection of subsets of S is a σ-algebra ($\mathbb{B}$) iff:
a. $\emptyset\epsilon\mathbb{B}$
b. $A\epsilon\mathbb{B} \implies A^c\epsilon\mathbb{B}$
c. $A_1, A_2, ...\epsilon\mathbb{B} \implies \bigcup_{n=1}^{\infty} A_n\epsilon\mathbb{B}$

Construction

S is finite/countable: $\mathbb{B} = \mathbb{P}(\mathbb{S})$ (Power Set of $\mathbb{S}$, all possible subsets of $\mathbb{S}$)

S is infinite/uncountable: Use Borel sets: $\mathbb{B} = \{(a,b), [a,b), [a,b]\}$ for $a < b$ and all countable $\cup$ and $\cap$ of those

Probability Functions

Axioms

Given $\mathbb{S}$ and σ-algebra, a probability function with domain $\mathbb{B}$ satisfies:
a. $P(A) \geq 0$ for all $A\epsilon\mathbb{B}$
b. $P(\mathbb{S}) = 1$
c. If $A_1, A_2, ...$ are pairwise disjoint, then $P(\bigcup_{n=1}^{\infty} A_n) = \sum_{n=1}^{\infty} P(A_n)$

Properties

1) $P(\emptyset) = 0$
2) $A \subseteq \mathbb{S} \implies P(A) \leq 1$
3) $P(A^c) = 1 - P(A)$
4) $P(B \cap A^c) = P(B) - P(A \cap B)$
5) $P(A \cup B) = P(A) + P(B) - P(A \cap B)$
6) $A \subseteq B \implies P(A) \leq P(B)$
7) Let $c_1, c_2, ...$ be a partition of $\mathbb{S}$ (ie. $c_i \cap c_j = \emptyset$ for $i \neq j$, $\bigcup_{i=1}^{\infty} c_i = \mathbb{S}$)
- $P(A) = \sum_{i=1}^{\infty} P(A \cap c_i)$
8) For any $A_1, A_2, ...$; $P(\bigcup_{i=1}^{\infty} A_i) \leq \sum_{i=1}^{\infty} P(A_i)$

Counting

Sampling

	w/o Repl.	**w/ Repl.**
Ordered Perm.	$\frac{n!}{(n-1)!}$	n^r
Unordered Comb.	$\frac{n!}{(n-r)!r!} : \binom{n}{r}$	$\binom{n+r-1}{r}$

Axioms

Enumerating equally likely outcomes (assume large but finite $\mathbb{S}, |\mathbb{S}| = N$). Want $P(A)$ where $A \subset \mathbb{S}, A\epsilon\mathbb{B}$
- $P(A) = \frac{\text{\# things in A}}{N}$

Product Rule:
- If a job consists of k separate experiments, the i^{th} of which can be done in n_i ways, then the job can be done in $n_1 * n_2 * ... * n_k$ ways

Sum Rule:
- If there are k events, the i^{th} of which can occur in n_i ways, then there are $n_1 + n_2 + ... + n_k$ to complete exactly 1 event
Inclusion/Exclusion: want to enumerate elements in $A : N_A = |A|$, sometimes easier to find:
- $N_{A^c} = |A^c| \therefore N_A = N - N_{A^c}$

Continous

Consider $\mathbb{S} \subset \mathbb{R}^d$ with uniform probability

Then for $A \subseteq \mathbb{S}, P(A) = \frac{\int_A ds}{\int_{\mathbb{S}} ds}$

Conditional Probability

If $A, B \subseteq \mathbb{S}$ and $P(B) > 0$;
$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(B|A)P(A)}{P(B)}$
Often use the law of total probability ($c_i \cap c_j = \emptyset$ for $i \neq j, \bigcup_{i=1}^{\infty} c_i = \mathbb{S}$):
$P(B) = \sum_{i=1}^{n} P(B|c_i)P(c_i)$

Independence

$A \perp\!\!\!\perp B$ iff $P(A|B) = P(A)$
$A \perp\!\!\!\perp B \implies A \perp\!\!\!\perp B^c, A^c \perp\!\!\!\perp B, A^c \perp\!\!\!\perp B^c$
Mutual Indepedence:
A collection of events $A_1, ..., A_n$ are mut. ind. if, for any subcollection of $A_{i_1}, ..., A_{i_k}$ we have:
- $P(\bigcap_{j=1}^{k} A_{i_j}) = \prod_{j=1}^{k} P(A_{i_j})$

Conditional Independence

A and B are conditionally independent given C if:
$P([A \cap B]|C) = P(A|C)P(B|C)$

Random Variables

Definition

A random variable (vector) is a function that maps from the sample space $\mathbb{S}$ to the real numbers $\mathbb{R}$
Formally: $X : \mathbb{S} \Rightarrow \mathbb{R}, \underset{\sim}{\boldsymbol{X}} : \mathbb{S} \Rightarrow \mathbb{R}$

Cumulative Distribution Function

The CDF of a random variable ($F_X(x)$) is defined as: $P(X \leq x)$ for all $x \epsilon \mathbb{R}$
a. $\lim_{x \to -\infty} F_X(x) = 0, \lim_{x \to \infty} F_X(x) = 1$
b. $F_X(x)$ is non-decreasing ie. for $x_i \leq x_2, F(x_1) \leq F(x_2)$
c. $F_X(x)$ is right-conitnuous ie. $\lim_{x \downarrow x_0} F_X(x) = F_X(x_0)$

Probability Density/Mass Function

A PMF is given by $f_X(x) = P(X = x)$
A PDFof a continuous random variable satisfies the following:
- $\int_{-\infty}^{x} f_x(t)dt$ for all $x \therefore f(X) = \frac{dF_x}{dx}$
- $P(a \leq x \leq b) = \int_a^b f_X(x)dx = P(a < x < b) = F(b) - F(a)$

A function is a valid PMF/PDF iff:
a) $f_X(x) \geq 0, \forall x$
b) $\sum_{x \epsilon X} f_X(x) = 1$ -OR- $\int_x f_X(x)dx = 1$

Kernel

Any non-negative function with a finite integral or sum can be made into a PDF or PMF
- $h(x) \geq 0 \forall x$
- $\int_{x \epsilon X} h(x)dx = k, 0 < k < \infty$
- $f_X(x) = \frac{1}{k}h(x)I_X(x)$

Common PDFs

Besides those given in the book:
- Survival Function: $S_X(x) = P(X > x) = 1 - F_X(x)$
- Hazard Function: $H_X(x) = \frac{f_X(x)}{S_X(x)}$
- Gamma Function: $\Gamma(\alpha) = \int_0^{\infty} t^{\alpha - 1}e^{-t}dt$
- - If α is an integer: $\Gamma(\alpha) = (\alpha - 1)!$
- - For general α: $\Gamma(\alpha + 1) = \alpha\Gamma(\alpha)$
- - Also: $\Gamma(\frac{1}{2}) = \sqrt{\pi}$

Expected Value

Definition

Given a random variable $g(x)$:

$$\mathbb{E}[g(x)] = \begin{cases} \int_{-\infty}^{\infty} g(x)f_X(x)dx, & \text{Continuous} \\ \sum_{x \epsilon X} g(x)f_X(x), & \text{Discrete} \end{cases}$$

Law of Unconscious Statistician: Let $Y = g(x)$
- $\mathbb{E}[g(x)] = \int_{-\infty}^{\infty} g(x)f_X(x)dx = \int_{-\infty}^{\infty} Yf_Y(y)dy = \mathbb{E}[Y]$

Probability as an Expectation:
$P(x \epsilon A) = \int_A f_X(x)dx = \int_{-\infty}^{\infty} I_A(x)f_X(x)dx = \mathbb{E}[I_A(x)]$

Properties of Expected Values

1) $\mathbb{E}[ax + b] = a\,\mathbb{E}[x] + b, \mathbb{E}[ag_1(x) + bg_2(x)] = a\,\mathbb{E}[g_1(x)] + b\,\mathbb{E}[g_2(x)]$
2) If $g(x) \geq 0, \forall x \epsilon X$, then $\mathbb{E}[g(x)] \geq 0$
3) If $g_1(x) \geq g_2(x), \forall x \epsilon X$, then $\mathbb{E}[g_1(x)] \geq \mathbb{E}[g_2(x)]$
4) If $a \leq g(x) \leq, \forall x \epsilon X$, then $a \leq \mathbb{E}[g(x)] \leq b$

Moments

Definition

For each interger n, the n^{th} moment of X is $\mathbb{E}[X^n]$

The n^{th} central moment is: $\mathbb{E}[X-\mathbb{E}[X]]^n$

Expected value is the first moment, Variance is the second central moment

Properties of Variance:
- $Var(aX+b) = a^2Var(X)$
- $Var(X) = \mathbb{E}[X^2] - (\mathbb{E}[X])^2$

Jensen's Inequality

Want to compare $\mathbb{E}[X]$ vs. $\mathbb{E}[Y]$ where $Y = g(X)$. Often can't directly compare.

$$JE : \begin{cases} \mathbb{E}[g(X)] \geq g(\mathbb{E}[X]), & g(x) \text{is convex} \\ \mathbb{E}[g(X)] \leq g(\mathbb{E}[X]), & g(x) \text{is concave} \end{cases}$$

How to tell if $g(x)$ is convex:
- Draw it (convex is bowl-shaped)
- Second Derivative: $g''(x) > 0 \implies$ convex

Moment Generating Function (MGF)

$$M_X(t) = \mathbb{E}[e^{tx}] = \begin{cases} \int\limits_{-\infty}^{\infty} e^{tx} f_X(x)dx, & X \text{is continuous} \\ \sum\limits_{x \epsilon X} e^{tx} f_X(x), & X \text{is discrete} \end{cases}$$

This holds if the expectation exists for t in the neighborhood of 0. That is, there exists an $h > 0$ such that $\mathbb{E}(e^{tx})$ exists for all $-h < t < h$

$\mathbb{E}[X^n] = M_X^{(n)}(0) = \frac{dn}{dt^n} M_x(t)|_{t=0}$

Characterizing Distributions

a) If X and Y have bounded support, $F_X(u) = F_Y(u)$ for all u iff $\mathbb{E}[X^r] = \mathbb{E}[Y^r]$, $r = 0, 1, 2, 3, ...$ (all moments are equal)
b) If MGF exists $M_X(t) = M_Y(t)$ for some t in neighborhood of 0, then $F_X(u) = F_Y(u)$ for all u

A sequence of random variables, $X_i, i = 1, 2, 3, ...$ each with an MGF $M_{X_i}(t)$. Further suppose $\lim\limits_{i->\infty} M_{X_i}(t) = M_x(t)$ for t in neighborhood of 0, and $M_x(t)$ is also an MGF
Then: there is a unique CDF $F_X(x)$ whose moments are determined by $M_x(t)$ and $\lim\limits_{(} i->\infty) F_{X_i}(x) = F_x(x)$

Basically, if the MGFs of RVs converge to an MGF, then the RVs themselves converge to the RV of the converged MGF

Lemma: Let $a_1, a_2, a_3 ...$ be a sequence of numbers such that $\lim\limits_{n\to\infty} a_n = a$
Then: $\lim\limits_{n\to\infty} (1 + \frac{a_n}{n})^n = e^a$

Theorem: Let $Y = aX = b \therefore M_Y(t) = e^{at} M_X(t)$

Transformations

Definition

X is a random variable, then $Y = g(X)$ is also a random variable. To find $P(Y)$ we need either $F_Y(y)$ or $f_Y(y)$
- $g(X)$ maps from $\mathbb{X}$ to $\mathbb{Y}$, basically $\mathbb{S} \to \mathbb{X} \to \mathbb{Y}$
- $\forall A, P(Y \epsilon A) = P(g(X) \epsilon A) = P(\{x \epsilon \mathbb{X} : g(x) = A\}) = P(X \epsilon g^{-1}(A))$

Discrete

$$f_Y(y) = \begin{cases} \sum\limits_{X \epsilon g^{-1}(y)} P(X = x), & Y \epsilon \mathbb{Y} \\ 0, & \text{otherwise} \end{cases}$$

Steps:
1) Find $\mathbb{Y}$
2) Identify $g^{-1}(y)$
3) Sum over appropriate x (if $g^{-1}(y)$ is a set with one element, $f_Y(y) = f_X(g^{-1}(y)))$

Continous

$$F_Y(y) = P(Y = y) = P(g(x) \leq y) = \int\limits_{x \epsilon \mathbb{X} : g(x) \leq y} f_X(x)dx$$

If $Y = g(X)$ is monotone, g^{-1} exists. If it's increasing, the inverse is as well (vise versa for decreasing)
If $g(X)$ is increasing, $F_Y(y) = F_X(g^{-1}(y))$. If $g(X)$ is decreasing, $F_Y(y) = -F_X(g^{-1}(y))$. In both:

$$f_Y(y) = \begin{cases} f_X(g^{-1}(y)) |\frac{d}{dy} g^{-1}(y)|, & y \epsilon \mathbb{Y} \\ 0, & \text{otherwise} \end{cases}$$

Steps:
1) Find $\mathbb{Y}$
2) Find $g^{-1}(y)$
3) Find $\frac{d}{dy} g^{-1}(y)$
4) Plug into $f_X(g^{-1}) |\frac{d}{dy} g^{-1}(y)$

If the transformation is non-monotonic, all you need to do is find the points of inflection and partition the transformation within ach region of monotinicty

Probability Integral Transform

NOT SURE IF REALLY NEED (7 Oct 2025)

Location Scale Family

Let $f_X(x)$ be a PDF and $\mu \epsilon \mathbb{R}, \sigma > 0$, then
$g(x) = \frac{1}{\sigma} f_X(\frac{x-\mu}{\sigma})$
This is the case when there exists a Z such that $X = \mu + \sigma Z$

MonteCarlo Integration

Write an integral as an expectation:
$I = \int\limits_a^b h(x)dx = \int\limits_a^b \frac{h(x)}{f_X(x)} f_X(x)dx = \mathbb{E}[\frac{h(x)}{f_X(x)} I_{(a,b)}(x)]$

Steps:
1) Simulate $x_1, ..., x_n$ from $f_X(x)$
2) Calculate $g(x_j) = \frac{h(x_j)}{f_X(x_j)} I_{(a,b)}^{(x_j)}, \forall j$
3) $\mathbb{E}[g(x)] \approx \frac{1}{n} \sum\limits_{j=1}^{n} g(x_j) \equiv \bar{g}$
$SE(\bar{g}_n) \approx \frac{1}{\sqrt{n}} s.d.(g(x_1), ..., g(x_n))$

Importance Sampling

FILL IN STUFF

Oct 30

Ex: $X|Z \sim N(Z, \sigma^2), Y|Z \sim N(Z, \sigma^2), (X \perp\!\!\!\perp Y)|Z$
We can say: $X = Z + \epsilon_X, Y = Z + \epsilon_Y : \epsilon_x, \epsilon_Y \sim N(0, \sigma^2), Z \sim N(\mu, \tau^2)$
$Cov(X, Y) = Cov(Z = \epsilon_X, Z + \epsilon_Y) = Cov(Z, Z) = Var(Z) = \tau^2$
For the correlation we need:
$Var(Y) = Var(Z) + Var(\epsilon_Y) = \tau^2 + \sigma^2$
$Var(X) = Var(Z) + Var(\epsilon_X) = \tau^2 + \sigma^2$
$Corr(X, Y) = \frac{Cov(X,Y)}{\sqrt{Var(X)}\sqrt{Var(Y)}} = \frac{\tau^2}{\tau^2+\sigma^2}$

Law of Total Covariance

For random variables X, Y, Z, with hierarchy as $(X|Y, Z), (Y|Z)$, and Z;
$Cov(X, Y) = \mathbb{E}[Cov(X, Y|Z)] + Cov(\mathbb{E}[X|Z], \mathbb{E}[Y|Z])$

Random Samples and Sums of Random Variables

Definition

The random variables $X_1, ..., X_n$ are a random sample of size n from population $f_X(x)$ if $X_i \overset{\text{iid}}{\sim} f_X(\cdot), i = 1, ..., n$

Joint PDF/PMF

$X_1, ..., X_n$ is a random sample. Since they are iid,
$f(x_1, ..., x_n) = \prod\limits_{i=1}^{n} f_X(x_i)$
Ex. Let $X_1, ..., X_n$ be the failure times in years of the i^{th} identical circiut components.
Assume $X_i \overset{\text{iid}}{\sim} Exp(\beta)$
Thus: $f(x_1, ..., x_n) = \prod\limits_{i=1}^{n} \frac{1}{\beta} e^{-x_i/\beta} = \frac{1}{\beta^n} e^{\frac{1}{\beta}\sum X_i}$

Use this to find:
$P(X_1 > 2, X_2 > 2, ..., X_n > 2) = [P(X_1 > 2)]^n = [1 - P(X_1 < 2)]^n = [1 - 1 + e^{\frac{-2}{\beta}}]^n = e^{\frac{-2n}{\beta}}$

Definition: Sampling Distribution - Let $X_1, ..., X_n$ be a random sample of size n. Let $T(X_1, ..., X_n)$ be a real-valued, real-vector function whose domain includes $\mathbb{X}$.
Then $T(X_1, ..., X_n)$ is a statistic and its distribution is a sampling distribution.

Common Statistics
$\bar{X} = \frac{1}{n} \sum\limits_{i=1}^{n} X_i$
$s^2 = \frac{1}{n-1} \sum\limits_{i=1}^{n} (X_i - \bar{X})^2$
Order statistics: media, range, etc.

Theorem: Let $x_1, ..., x_n$ be any numbers and $\bar{x} = \frac{1}{n} \sum\limits_{i=1}^{n} x_i$ then:
a. $\underset{a}{min} \sum\limits_{i=1}^{n} (x_i - a)^2 = \sum\limits_{i=1}^{n} (x_i - \bar{x})^2$ -or- $\bar{x} = \underset{a}{argmin} \sum_i = 1^n (x_i - a)^2$
b. $(n-1)s^2 = \sum\limits_{i=1}^{n} (x_i - \bar{x})^2 = \sum\limits_{i=1}^{n} x_i^2 - n\bar{x}^2$

Theorem: Let $Z_1, ..., X_n$ be a random sample with population mean and variance μ, σ^2, then:
1) $\mathbb{E}(\bar{X}) = \mu$
2) $Var(\bar{X}) = \frac{\sigma^2}{n}$
3) $\mathbb{E}(s^2) = \sigma^2$

2 Dec 2025

Convergence in r^{th} mean

A sequence of r.v. $X_1, X_2 ...$ converges to X in r^{th} mean if $\lim\limits_{n\to\infty} \mathbb{E}(|X_n - X|^r) = 0$
Written as: $X_n \xrightarrow{L^r} X$
Proof: Assume $X_n \xrightarrow{L^r} X$. We know then that $\lim\limits_{n\to\infty} \mathbb{E}(|X_n - X|^r) = 0$.
By Chebychev's, $\lim\limits_{n\to\infty} P(|X_n - X| > \epsilon) = \lim\limits_{n\to\infty} P(|X_n - X|^r > \epsilon^r) \leq \lim\limits_{n\to\infty} \frac{\mathbb{E}(|X_n - X|^r)}{\epsilon^r} = 0$
Ex. Let $U \sim Unif(0, 1)$
$X_1 = I_{[0,1]}^{(u)}$
$X_2 = I_{[0,1/2]}^{(u)}, X_3 = I_{[1/2,1]}^{(u)}$
$X_4 = I_{[0,1/3]}^{(u)}, X_5 = I_{[1/3,2/3]}^{(u)}, X_6 = I_{[2/3,1]}^{(u)} \cdots$
We showed previously that $X_n \xrightarrow{P} 0$ but $X_n \not\xrightarrow{a.s.} 0$
What about $X_n \xrightarrow{L^r} 0$?
Well, $\lim\limits_{n\to\infty} \mathbb{E}(|X_n - 0|^r) = \lim\limits_{n\to\infty} \mathbb{E}((X_n)^r)$

X_n will either be 0 or 1, depending on the $Unif()$. Thus, $= \lim_{n\to\infty} \mathbb{E}((X_n))$.
We know $\mathbb{E}(X_2) = P(0 < u < 1/2) = 1/2)$. This can be applied to all X_n's.
Thus $= \lim_{n\to\infty} h(n) = 0$.

Thus the limit goes to 0, which then means that $X_n \xrightarrow{L^r} 0$. This also implies $X_n \xrightarrow{P} 0$

If $s > r \geq 1$ then $X_n \xrightarrow{L^s} X \implies X_n \xrightarrow{L^r} X$

Convergence in Distribution

A sequence of r.v. $X_1, X_2...$ converges in distribution to r.v. X if $\lim_{n\to\infty} F_{X_n}(x) = F_X(x)$ at all points x where $F_X(x)$ is continuous.
$X_n \xrightarrow{D} X$ is implied by all the other convergences (probability, almost surely, and r^{th} means).
Ex. $X_1, X_2, ... \overset{\text{iid}}{\sim} Unif(0,1)$. Let's examine $X_{(n)}$ as $n \to \infty$.
Recall that:
$F_{X_{(n)}}(x) = \begin{cases} 0, & x < 0 \\ x^n, & x \in [0,1) \\ 1, & x \geq 1 \end{cases}$
$lim_{n\to\infty} F_{X_{(n)}}(x) = \begin{cases} 0, & x < 0 \\ lim_{n\to\infty} x^n, & x \in [0,1) \\ 1, & x \geq 1 \end{cases} = \begin{cases} 0, & x < 1 \\ 1, & x \geq 1 \end{cases}$
Note that this is the CDF for a point mass (step function) at 1, so $X_{(n)} \xrightarrow{D} 1$.
Theorem: For a sequence of random variables $X_{(n)} \xrightarrow{P} C$ iff $X_{(n)} \xrightarrow{D} C$
In words, $P(|X_n - C| > \epsilon) \to 0 \forall \epsilon$ is equivalent to
$lim_{n\to\infty} F_{X_{(n)}}(x) = \begin{cases} 0, & x < 1 \\ 1, & x \geq 1 \end{cases}$

0.1 Slowing Down Convergence

Sometimes it is helpful to 'slow down' convergence so the limiting distribution isn't a constant.
As an example, consider $Y_n = n(1 - X_{(n)})$
$F(Y_n) = P(Y_N \leq y) = P(n(1 - X_{(n)})) = P(1 - \frac{y}{n} \leq X_{(n)}) = 1 - P(X_{(n)} \leq 1 - \frac{y}{n}) = 1 - (1 - \frac{y}{n})^n$
Thus, $lim_{n\to\infty} F(Y_n) = lim_{n\to\infty} 1 - (1 - \frac{y}{n})^n = 1 - lim_{n\to\infty}(1 - \frac{y}{n})^n = 1 - e^{-y}$
Thus $Y_n \xrightarrow{D} Y \sim Exp(1)$

0.2 Central Limit Theorem

Consider $X_n = \frac{1}{n}\sum_{i=1}^{n} X_i$ for a sequence $X_1, X_2, ...$

We have shown: $\bar{X}_n \xrightarrow{P} \mu$, $\bar{X}_n \xrightarrow{a.s.} \mu$
Let $X_1, X_2, ...$ be a seuqnce of iid r.v. whose MGFs exist in a neighborhood of 0. Let $\mathbb{E}(X_i) = \mu$, $Var(X_i) = \sigma^2 > 0$.
Let $X_n = \frac{1}{n}\sum_{i=1}^{n} X_i$. Let $G_n(x)$ be the CDF of $\frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma}$ or $\frac{\bar{X}-\mu}{\sigma/\sqrt{n}}$
Then for any $x \in \mathbb{R} : lim_{n\to\infty} G_n(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} e^{\frac{1}{2}y^2} dy =$ CDF of Standard Normal.
Thus, $\frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} \xrightarrow{D} N(0,1)$, or $Z_n = \frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma}$ and $Z \sim N(0,1), Z_n \xrightarrow{D} Z$
Proof: Let $Y_i = \frac{X_i - \mu}{\sigma}$, $\mathbb{E}(Y_i) = 0$, $Var(Y_i) = 1$.
$\frac{1}{n}\sum_{i=1}^{n} Y_i = \frac{1}{\sqrt{n}}\sum_{i=1}^{n}\left(\frac{X_i - \mu}{\sigma}\right)$
$= \frac{1}{\sigma\sqrt{n}}\left(\sum_{i=1}^{n} X_i - n\mu\right) = \frac{1}{\sigma\sqrt{n}}(n\bar{X}_n - n\mu)$
$= \frac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} = Z_n$
By Thm. 2.3.15, Thm 4.6.7, $M_{Z_n}(t) = \left[M_Y(\frac{t}{\sqrt{n}})\right]^n$