```
B(R) = o-field senerated by interval (3,6)
                 6 (6) smallest field contains all elements of outcomes
                                                                                                                         AcF(S) - AeF(S)
                                                               collection of subsets of S
                 Random experiment characterized by {S, F, P}
  Session 1
                  Event space F satisfies closure property —
 Session 2
                 Probability mapping P satisfies axiom of probability \begin{cases} P(A_i) \ge 0 & P(S) = 1 \\ P(A_i \cup A_i) = P(A_i) + P(A_i) \end{cases}
                                                                           P(A(UA)=P(A)+P(A) for disjoint A, , Aze F(s)
 Session 3
                   F(s) \longrightarrow [0,1]
                  In case of countable S, P is called probability mass function (PMF)
 Session 5
                 In case of uncountable S, P is called probability density function (PDF)
                  Conditional probability P(A|B) = P(A \cap B) Total probability law P(B) = \sum_{l=1}^{N} P(B|A_l) P(A_l)
Bayes formula P(A|B) = P(B|A) P(A) P(B) S = S_1 \times S_2 F = \sigma(SA \times B) VA \in F_1 and V \in F_2
 Session 6
                                                                              S = S_1 \times S_2 F = \sigma(\{A \times B \mid VA \in F, \text{ and } VB \in F_2\})

P is generated according to axiom of probability
                  Given (S, F, P,) and (S, F, P).
 Session 7
                   We can form combined experiment (S, F, P) with ) such that P(A×S,) = P(A) for VAEF,
                   Extension to n-combined experiment is straightforward | P(S, xB) = P(B) for YBEF,
                   Random variable X(\cdot) is a mapping from S to R. (S,F,P) \xrightarrow{X(\cdot)} (IR,B(R),Px)
 Sassion 10
                  Being Borel measurable function (such that X-(A) = \ w & S | X(w) = A & F \ for VA & B(R))
                    ensures that we can compute P_X(A) = P(X \in A) = P(\{w \in S \mid X(w) \in A\})
                  Cumulative distribution function (CDF) F_{x}(x) = P_{x}((-\infty, x]) = P(x^{-1}((-\infty, x]))
 Session 11
                  RV is continuous if F_{x}(x) is a continuous function over x and \frac{dF_{x}(x)}{dx} = f_{x}(x)
  Session 12
                  Function of RV Y=g(X) is valid RV if \prod domain of g contains range of X
  Session 15
                                                                \mathbb{Z} \quad \mathbb{R}_{x} \text{ is Borel set } \mathbb{Z} \quad \mathbb{P}(\{g(X=+\infty)\}) = 0
                  E[X] = \int_{-\infty}^{\infty} g(x) f_{x} \cos dx
  Session 16
                 E[X|M] = \int_{-\infty}^{\infty} x f_{x}(x|M) dx \qquad Var[X] = \int_{-\infty}^{\infty} (x-\overline{x})^{2} f_{x}(x) dx \qquad f_{x}(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{i\omega x} f_{x}(x) dx
Characteristic function of X = \int_{-\infty}^{\infty} e^{i\omega x} f_{x}(x) dx
 Session 18
                   \Phi_{x}(w) = f_{y}(w) \longrightarrow X and Y are identical but f_{x}(x) = f_{y}(y) \longrightarrow X and Y are identical
                    If T-ax+b & Pr(w) = einb pr(aw)
                  Moment generating function of X = \frac{1}{x} (s) is E[e^{sx}] = \int_{-\infty}^{e^{sx}} f_{x}(x) dx E[X^{n}] = \frac{d^{n} \Phi_{x}(s)}{ds^{n}}|_{s=0}
                                                                                    Characteristic
                  Type PMF
                                                   Type
                                                                  CDF
                  Uniform
                                                  Uniform
                                                                                                        \sin(\theta_1 + \theta_2) = \sin\theta_1 \cos\theta_2 + \cos\theta_1 \sin\theta_2
                             (") pk (1-p)" - Exponential he-xx
                 Binomial
                                                                                                       sin (0, -02) = sino, cos 02 - cos 0, sin 02
np npct-p)
                                                                                      e iwh e-1202 cos (0,+02) = cos 0, cos 02 - sin 0, sin 02
                                                Gaussian \frac{1}{12\pi\sigma^2}e^{\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)}
                 Geometric pk(1-p)
                                                                                                       COS (0,-02) = COSO, COSO2 + Sin 0, Sin 02
                Poisson \lambda^k e^{-\lambda}
                                                 Cauchy
```

```
rect(t) -> six(f)
           Fourier Transform
                                                                                                                                                    1 0 S(f)
                                                                                                                                           S(t) => 1
S(t-to) => e-into
                                                                                                                                                                                                                                  cos(enfot) => = (sif-fo)+sif+fo)
                   fits = I for Frus ent du
                                                                                                                                                                                                                                                                                                                                                                                        e out = atim
                   F(w) = 100 f(t) e int dt eienfet => Sif-fo) sin (271 fet) => 1 (84-fo) -8(f+fo)) Poisson process

\frac{1}{2\pi \sigma_{1}^{2}} \left( \frac{x_{1}y_{1}}{2} \right) = \frac{1}{2\pi \sigma_{1}^{2}} \left[ \frac{1}{2(1-r^{2})} \left[ \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} - \frac{2r(x_{1}-\mu_{x})(y_{1}-\mu_{y})}{\sigma_{y}^{2}} + \frac{(y_{1}-\mu_{y})^{2}}{\sigma_{y}^{2}} \right] \right] = \frac{1}{2\pi \sigma_{1}^{2}} \left[ \frac{1}{2(1-r^{2})} \left[ \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} - \frac{2r(x_{1}-\mu_{x})(y_{1}-\mu_{y})}{\sigma_{y}^{2}} + \frac{(y_{1}-\mu_{y})^{2}}{\sigma_{y}^{2}} \right] \right] = \frac{1}{2\pi \sigma_{1}^{2}} \left[ \frac{1}{2(1-r^{2})} \left[ \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} - \frac{2r(x_{1}-\mu_{x})(y_{1}-\mu_{y})}{\sigma_{y}^{2}} + \frac{(y_{1}-\mu_{y})^{2}}{\sigma_{y}^{2}} \right] \right] = \frac{1}{2\pi \sigma_{1}^{2}} \left[ \frac{1}{2(1-r^{2})} \left[ \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} - \frac{2r(x_{1}-\mu_{x})(y_{1}-\mu_{y})}{\sigma_{y}^{2}} + \frac{(y_{1}-\mu_{y})^{2}}{\sigma_{y}^{2}} \right] \right] = \frac{1}{2\pi \sigma_{1}^{2}} \left[ \frac{1}{2(1-r^{2})} \left[ \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} - \frac{2r(x_{1}-\mu_{x})(y_{1}-\mu_{y})}{\sigma_{y}^{2}} + \frac{(y_{1}-\mu_{y})^{2}}{\sigma_{y}^{2}} \right] \right] = \frac{1}{2\pi \sigma_{1}^{2}} \left[ \frac{1}{2(1-r^{2})} \left[ \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} - \frac{2r(x_{1}-\mu_{x})(y_{1}-\mu_{y})}{\sigma_{y}^{2}} + \frac{(y_{1}-\mu_{y})^{2}}{\sigma_{y}^{2}} \right] \right] = \frac{1}{2\pi \sigma_{1}^{2}} \left[ \frac{1}{2(1-r^{2})} \left[ \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} - \frac{2r(x_{1}-\mu_{x})(y_{1}-\mu_{y})}{\sigma_{y}^{2}} + \frac{(y_{1}-\mu_{y})^{2}}{\sigma_{y}^{2}} \right] \right] = \frac{1}{2\pi \sigma_{1}^{2}} \left[ \frac{1}{2(1-r^{2})} \left[ \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} - \frac{2r(x_{1}-\mu_{x})(y_{1}-\mu_{y})}{\sigma_{y}^{2}} + \frac{(y_{1}-\mu_{y})^{2}}{\sigma_{y}^{2}} \right] \right] = \frac{1}{2\pi \sigma_{1}^{2}} \left[ \frac{1}{2(1-r^{2})} \left[ \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} - \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{y}^{2}} + \frac{(y_{1}-\mu_{y})^{2}}{\sigma_{y}^{2}} \right] \right] = \frac{1}{2\pi \sigma_{1}^{2}} \left[ \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} + \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} + \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} \right] = \frac{1}{2\pi \sigma_{1}^{2}} \left[ \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} + \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} + \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} \right] = \frac{1}{2\pi \sigma_{1}^{2}} \left[ \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} + \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} + \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} + \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} \right] = \frac{1}{2\pi \sigma_{1}^{2}} \left[ \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} + \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} + \frac{(x_{1}-\mu_{x})^{2}}{\sigma_{x}^{2}} + \frac{(x_{1}-\mu_{x})^{2}}{\sigma
                                                     Two RVs are statistically independent if f_{XY}(x,y) = f_X(x) f_Y(y) = f_X(x,y) \begin{vmatrix} \frac{\partial x}{\partial x} & \frac{\partial x}{\partial w} \\ \frac{\partial y}{\partial x} & \frac{\partial y}{\partial w} \end{vmatrix}
    Session 20
                                                     Joint density determination Z = f(X,Y) and W = g(X,Y) \rightarrow \int_{\mathbb{R}^{N}} (z,w) = \int_{XY} (x,y) \left| \frac{\partial(x,y)}{\partial(z,w)} \right| J(x,y)
   Session 21
                                                     Correlation E[XY] Correlation coefficient = E[(X-X)(Y-Y)] This is 0 if RVs are uncorrelated.
   Se ssion 23 E[X^{j}Y^{k}] = \frac{\partial^{j}\partial^{k}}{\partial s_{i}^{j}\partial s_{k}^{k}} \Phi_{xy}(s_{i},s_{i})
E_{xy}[g(x,y)] = E_{x}[E_{y}[g(x,y)|x]]
                                                                                                                                                                                                                                                                                                 \begin{bmatrix} E_{\gamma} \mid g(X_1 \mid Y_1) \mid X \end{bmatrix} = \begin{cases} \chi(x_1 \mid X_2) \dots \end{pmatrix} \begin{vmatrix} \frac{\partial}{\partial x_1} & \frac{\partial}{\partial x_1} \\ \frac{\partial}{\partial x_2} & \frac{\partial}{\partial x_2} \\ \vdots & \ddots & \vdots \\ \frac{\partial}{\partial x_n} & \frac{\partial}{\partial x_n} & \frac{\partial}{\partial x_n} \end{vmatrix}
                                                     Random vector X = (X_1, X_2, X_3, ...) is a mapping from S to \mathbb{R}^n
   Session 24
                                                     Given \underline{\mathcal{K}} = (x_1, x_2, x_3, ...) and \underline{\mathcal{K}} = (y_1, y_2, y_3, ...) f_{\underline{\mathcal{K}}}(y_1, y_2, y_3, ...) = f_{\underline{\mathcal{K}}}(x_1, x_2, x_3, ...) \frac{\partial (x_1, x_2, x_3, ...)}{\partial (y_1, y_2, y_3, ...)}

Correlation matrix R = \begin{pmatrix} E[x_1, x_1] & E[x_1, x_2] & ... & E[x_1, x_2] \\ E[x_2, x_1] & ... & E[x_1, x_2] \end{pmatrix}

Characteristic function
                                                     Covariance matrix C = \begin{pmatrix} E[(x_1 - \overline{X_1})(x_1 - \overline{X_1})] & E[(x_1 - \overline{X_1})(x_2 - \overline{X_2})] & \cdots \\ E[(x_2 - \overline{X_2})(x_1 - \overline{X_1})] & \cdots \end{pmatrix} \qquad \overrightarrow{\Phi}_{\underline{X}}(\Omega) = E[e^{i\Omega \cdot \underline{X}^T}]
      Session 27 Sequence of RVs \{X_n\} = X_1, X_2, X_3, ... converges to X if there exist neN such that |X_n - X| < \varepsilon for \forall \varepsilon > 0
                                                                                        ( everywhere X (w), X2 (w), ... converges to X (w) for each w
                                                converge almost everywhere P(\{X_n \to X\}) = 1

mean scuare E[|X_n - X|^2] \to 0

in probability P(\{|X_n - X| > E\}) \to 0 as n \to \infty

In distribution F_{X_n}(x) \to F_{X_n}(x) as n \to \infty
                                                                                    In density f_{x_n}(x) \rightarrow f_{x_n}(x) as n \rightarrow \infty
      Chebyshev inequality P(\{|x-\mu|>\epsilon\}) \leq 5/\epsilon^2 = f_{*(t_1+c)*(t_2+e)}, (x_1, x_2, x_3, ...)
Session 28 Random Stochastic Process **(t) | Rxs \rightarrow | R
                                                    RP is strict sense stationary if n-order are invariant to time \{x_1, x_2, x_3, \dots\}

RP is wide sense stationary if n-order depends on time difference

\prod E[x(t)] = X

E[x(t)] = R_{**}(t-t_2)
                                                      Autocorrelation of RP X(t) is Rxx (t, t2) = E[X(t) X(t2)]
                                                     Autocovariance of RP X(t) is Cxx (t, t2) = E[(X(t, )-M(t, )(X(t2)-M2(t2))]
                                                    Characteristic function Gaussian RP is $\int \tilde{\pi(t) \tilde{\pi(t)} \tilde{
                                                      x(t) -> y(t) } satisfying { [] L[x,ct)+x,ct)]=L[x,ct)]+L[x,ct)] WSS/SSS input LTI ws3/SSS x(t+c) -> y(t+c) } satisfying { [] L[x,ct)]=A·L[x(t)] Gaussian input -> Gaussian input -> Gaussian
   Session 29
                                                                                                                                                                                                                                                                                                            Rxx = 1 100 Sxx(w) e int del
                                                       E[L[x(t)]] = L[E[x(t)]]
                                                      Power spectral density Sxx(w) = IRxx(t) e lut dt
Sessibn 30
                                                                                                                                                                                                                                                                                                                        white noise process has Courtition=0
                                                       If How = 10 hot eint dt, Syow = Sxx cw) How 12
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