Final Topics.

1. Generating functions.

LOCAL LIMIT THEOREM.

 $S_n = X_1 + X_2 + \ldots X_n$ where X_j are iid, $X_j \sim X$, EX = 0, $VX = \sigma^2$. Let

$$\phi(x) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{z^2}{2\sigma^2}\right)$$

Theorem. (Lattice LLT) If X has lattice distribution with span h, so that $X \in b + h\mathbb{Z}$ then for any $x_n \in bn + h\mathbb{Z}$ such that $x_n/sqrtn \to z$ we have

$$\frac{\sqrt{n}P(S_n = x_n)}{h} \to \Phi(z)$$

Theorem. (Non-lattice LLT) If X has non-lattice distribution then for any $x_n \in bn + h\mathbb{Z}$ such that $x_n/sqrtn \to z$ for any a, b we have

$$\frac{\sqrt{nP(S_n \in (x_n + a, x_n)}}{h} \to (b - a)\Phi(z).$$

RECURRENCE OF RANDOM WALKS.

Therem. Let $S_n = X_1 + X_2 \dots X_n$ where X_j are iid and $X_j \sim X$ and $E|X| < \infty$. (a) Suppose that X is integer valued and considered as a Markov process on \mathbb{Z} , S_n is irreducible and aperiodic. Then S_n is recurrent if and only if EX = 0.

(b) Suppose that X is non lattice, then the following conditions are equivalent. (i) EX = 0.

(1) EX = 0.

(ii) For any interval I, S_n visits I infinitely many times.

BRANCHING PROCESSES.

$$Z_{n+1} = \sum_{j=1}^{Z_n} X_{jn}$$

where $Z_0 = 1$, X_j are iid, $X_j \sim X$, $\operatorname{Var} X > 0$. Let p be the extinction probability

$$p = \lim_{n \to \infty} P(Z_n) = 0.$$

Theorem. If $EX \leq 1$ then p = 1. If EX > 1 then p is the smallest root of $p = G_X(p)$ where $G_X(s)$ is the generating function of X.

2. Markov chains.

n-STEP TRANSITION PROBABILITIES. $P(n) = P^{n}. P(n+1) = PP(n) = P(n)P. \pi(n) = \pi(0)P^{n}.$ CLASSIFICATION OF STATES. **Theorem.** (a) *j* is transient iff $\sum_{n} p_{jj}(n) < \infty$. (b) *j* is not positively recurrent iff $p_{jj}(n) \to 0$. (c) If *j* is transient then $P(X \text{ returns } j \ n \text{ times} | X_{0} = j) = p^{n}(1-p).$ CLASSIFICATION OF CHAINS. **Theorem.** (a) If $i \leftrightarrow j$ then *i* and *j* have the same period. (b) If $i \leftrightarrow j$ then *i* and *j* are of the same type. (c) If $i \rightarrow j$ and *j* is transient then *i* is transient. (d) If $i \rightarrow j$ and *i* is recurrent then $j \rightarrow i$. **Decomposition Theorem.** $S = T \bigcup C_1 \bigcup C_2 \cdots \bigcup C_n \ldots$ where *T* consists of

Decomposition Theorem. $S = T \bigcup C_1 \bigcup C_2 \cdots \bigcup C_n \ldots$ where T consists of transient states and C_j are closed recurrent subchains.

 $C_j = \bigcup_{l=1}^{n_j} C_{jl}$ where $X_0 \in C_{jl} \Rightarrow X_n \in C_{j;(l+n) \mod n_j}$ and X_{n_jk} restricted to C_{jl} is irreducible and aperiodic.

STATIONARY DISTRIBUTION AND LIMIT THEOREMS.

Theorem An irreducible chain has a stationary distribution iff it is positively recurrent. In this case $\pi_j = \mu_j^{-1}$ where μ_j is the mean recurrence time.

Theorem (a) An irredicible chain is positively recurrent iff there exists positive summable solution to the equation x = xP.

(b) Let s be an element of an irreducible chain. The chain is transient iff there exists a non-zero solution y_j satisfying $|y_j| \leq 1$ to the equation

$$y_i = \sum_{j \neq s} p_{ij} y_j$$

Theorem. (a) If the chain is irreducible an aperiodic then $p_{ij}(n) \to \mu_j^{-1}$ (where $\infty^{-1} = 0$).

(b) For an arbitrary irreducible chain

$$\frac{1}{N}\sum_{n=1}^{N}p_{ij}(n) \to \mu_j^{-1}.$$

CHAINS WITH FINITELY MANY STATES.

Theorem. (a) In a finite chain j every recurrent state is positively recurrent. (b) j is positively recurrent iff $j \to i$ implies $i \to j$.

Theorem. In a finite irreducible aperiodic chain there exist constants C > 0and $\theta < 1$ such that $|p_{ij}(n) - \pi_j| \leq C\theta^n$.

POISSON PROCESS.

Poisson process with intensity λ :

 $S_n = \sum_{j=1}^n X_j$ where X_j are iid, $X_j \sim \text{Exp}(\lambda)$. $N(t) = \max(n : S_n \leq t)$. N(t)-Poisson (λ) iff N(0) = 0 N has independent increments and

$$P(N(t+h) - N(t) = k) = \begin{cases} 1 - \lambda h + o(h) & \text{if } k = 0\\ \lambda h + o(h) & \text{if } k = 1\\ o(h) & \text{if } k > 1 \end{cases}$$

Let (X, μ) be a measure space. A point X-valued process is Poisson process with intensity measure μ if letting N(A) to denote the number of points in A we have (i) N(A) has Poisson $(\mu(A))$ distribution.

(ii) If $A_1, A_2 \dots A_n$ are disjoint then $N(A_1), N(A_2) \dots N(A_n)$ are independent. **Theorem** (a) If $\{x_j\}$ is a Poisson process on X with intensity μ and $f: X \to Y$ is a measurable map then $\{f(x_j)\}$ is a Poisson process on Y with intensity $\nu(B) = \mu(f^{-1}B)$.

(b) If N_1 and N_2 are independent Poisson processes with intensities μ_1 and μ_2 then $N = N_1 + N_2$ is a Poisson process with intensity $\mu = \mu_1 + \mu_2$.

(c) If N is a Poisson process with intensity μ and we discard the point x with probability p(x) then the remaining points form Poisson process with intensity ν where

$$\nu(A) = \int_A p(x) d\mu(x).$$

Campbell-Hardy Theorem. Let $\{x_j\}$ be a Poisson process of \mathbb{R} with intensity λ Let W_j be iid random variables independent of the Poisson process and r be a

 $\mathbf{2}$

smooth function. Let

$$G(t) = \sum_{x_j > 0} r(t - x_j) W_j.$$

Then

$$E\left(\exp(i\theta G(t))\right) = \exp\left(\lambda \int_0^t e^{i\theta r(s)W} ds\right).$$

BIRTH AND DEATH CHAIN.

Let $p_{n(n+1)} = p_n$, $p_{n(n-1)} = q_n$ and $p_{nj} = 0$ for $j \neq n \pm 1$. **Theorem.** Let $\xi_n = \frac{p_0 p_1 \dots p_{n-1}}{q_1 q_2 \dots q_n}$. The process is positively recurrent iff $S = \sum_n \xi_n < \infty$. In this case $\pi_j = \xi_j / S$. **Theorem.** Let $\eta_j = \frac{q_1 q_2 \dots q_j}{p_1 p_2 \dots p_j}$. The process is recurrent if $\sum_{j=0}^{\infty} \eta_j = \infty$. CONTINUOUS TIME CHAINS. Forward counting $D'_{n-1} = DC$.

Forward equation P' = PG.

Backward equation P' = GP.

Transition probabilities and the generator $P(t) = \exp(tG)$.

Stationary distribution $\pi G = 0$.

Theorem. Suppose that $p_{ij}(t) \to \delta_{ij}$ as $t \to 0$ and that the chain is irreducible. (a) If there exist stationary distribution then $p_{ij}(t) \to \pi_j$ as $t \to \infty$.

(b) If there is no stationary distribution then $p_{ij}(t) \to 0$ as $t \to \infty$.

Theorem. Suppose that either $|g_{ii}|$ are uniformly bounded or for each *i* there are only finitely many j such that $g_{ij} \neq 0$. Then

(a) The holding time at state *i* has $Exp(-g_{ii})$ distribution.

(b) The probability that the first jump from state *i* is to state *j* equals $g_{ij}/|g_{ii}|$.

3. Stationary processes.

LINEAR PREDICTION.

Theorem. Let X_n be a real stationary sequence with zero mean and covariance c(m). Then the best linear predictor of X_{r+k} based on $X_r, X_{r-1} \dots X_{r-s}$ takes form

$$\hat{X}_{r+k} = \sum_{j=0}^{s} a_j X_{r-j}$$

where

$$\sum_{j=0}^{n} a_j c(|m-j|) = c(k+m) \text{ for } m = 0, 1 \dots s.$$

Spectral Density.

Continuous time Bochner Theorem. The following are equivalent (a) c(t) is a covariance function of a weakly stationary process;

(b) For any real $t_1, t_2 \dots t_n$ and $z_1, z_2 \dots z_n$

$$\sum_{jk} c(t_j - t_k) z_j \bar{z}_k \ge 0.$$

(c) There exists a measure μ on \mathbb{R} such that

$$c(t) = \int_{-\infty}^{\infty} e^{it\lambda} d\mu(\lambda)$$

Discrete time Bochner Theorem. The following are equivalent (a) c(n) is a covariance function of a weakly stationary process;

(b) For any real $m_1, m_2 \dots m_n$ and $z_1, z_2 \dots z_n$

$$\sum_{jk} c(m_j - m_k) z_j \bar{z}_k \ge 0$$

(c) There exists a measure μ on $(-\pi, \pi]$ such that

$$c(t) = \int_{-\pi}^{\pi} e^{it\lambda} d\mu(\lambda).$$

ERGODIC THEOREM.

Ergodic Theorem for stationary sequences. If X_n is a weakly stationary sequence then there exists a mean square limit

$$\bar{X} = \frac{1}{N} \lim_{n=1}^{N} X_n.$$

If X_n is strongly stationary then also $X_n \to \overline{X}$ with probability 1.

If the spectral measure satisfies $\mu(\{0\}) = 0$ then $\overline{\hat{X}} = EX$.

Ergodic Theorem for measure preserving transformations. Let T be a transformation of space Ω preserving a probability measure μ . Let f be a square integrable observable. Then there exists a square integrable observable $\bar{f}(\omega)$ such that

$$\frac{1}{N}\sum_{n=1}^{N}f(T^{n}\omega)$$

converges to $\bar{f}(\omega)$ in mean squares and with probability 1.

If any T-invariant set A has measure either 0 or 1 then $\bar{f}(\omega) = Ef$.

4. Renewal Theory.

$$S_n = X_1 + X_2 \dots + X_n$$

where X_n are positive iid with distribution F. Let $\mu = EX$, $N(t) = \max(n : S_n \leq t)$, m(t) = E(N(t)), $F_k = F * F\dot{F}$ (k times).

$$m(t) = \sum_{k=1}^{\infty} F_k(t).$$

RENEWAL EQUATION.

$$\mu = H + \mu * F \Rightarrow \mu = H + H * m.$$

LIMIT THEOREMS FOR THE RENEWAL PROCESS. **Theorem.** (a) $N(t)/t \rightarrow \frac{1}{\mu}$ almost surely. (b) If $\sigma^2 = Var(X)$ satisfies $0 < \sigma^2 < \infty$ then

$$\frac{N(t) - t/\mu}{\sqrt{t\sigma^2/\mu^3}} \Rightarrow \mathcal{N}(0, 1)$$

Renewal Theorems.

Discrete Renewal Theorem. If X is integer valued and has span 1 then

$$P(\exists n: S_n = m) \to \frac{1}{\mu}$$

as $m \to \infty$.

Renewal Theorem. (a) $m(t)/t \to \frac{1}{\mu}$.

(b) If X is non-lattice then for any positive integrable non-increasing function g

$$g * m \to \frac{1}{\mu} \int_0^\infty g(s) ds$$

(c) If $V(X) = \sigma^2 < \infty$ then

$$\lim_{t \to \infty} \left(m(t) - \frac{t}{\mu} \right) = \frac{\sigma^2 - \mu^2}{2\mu^2}.$$

Let $\rho = ES/EX$ and $U_n = S_n - X_{n+1}$. Let W_n be the waiting time of *n*-th customer.

Theorem. (a) If $\rho \ge 1$ then $P(W_n < z) \to 0$ as $n \to \infty$. (b) If $\rho < 1$ then as $n \to \infty W_n$ converges in distribution to

$$\max_{m\geq 0}\sum_{j=1}^m U_j.$$

6. Optimal Sampling.

Wald's equation. If X_j are iid and M is a stopping time then

$$E\left(\sum_{n=1}^{M} X_j\right) = EXEM.$$

Martingale Sampling. If (Y_n, F_n) is a martingale and T is a stopping time such that

 $\begin{array}{l} \text{(a)} \ P(T<\infty)=1;\\ \text{(b)} \ P(|Y_T|)<\infty;\\ \text{(c)} \ E(Y_n \mathbf{1}_{n>T})\to 0 \ \text{as} \ n\to\infty \ \text{then} \\ E(Y_T|F_0)=Y_0. \end{array}$

7. DIFFUSION PROCESSES.

Maximum of Brownian Motion. Let W(t) be a Brownian Motion with zero drift and variance t. Let $M(t) = \sum_{s \in [0,t]} W(s)$, $\tau(x) = \min(t : W(t) = x)$. Then for x > 0

$$P(M(t) > x) = P(\tau(x) < t) = \frac{1}{2}P(W(t) > x).$$

Arc Sine Law.

$$P(W(t) \text{ has no zeros on } [t_0, t_1]) = \frac{2}{\pi} \sin^{-1} \left(\sqrt{t_0/t_1} \right)$$

Diffusions.

Let X(t) be a diffusion process with drift a(t, x) and diffusion coefficient b(t, x). Let $p((s, x) \to (t, y))$ be transition density of X(t).

Forward equation.

$$\frac{\partial p}{\partial t} = -\frac{\partial}{\partial y} \left[a(t,y)p(t,y) \right] + \frac{1}{2} \frac{\partial^2}{\partial y^2} \left[b(t,y)p(t,y) \right].$$

Backward equation.

$$\frac{\partial p}{\partial s} = -a(s,x)\frac{\partial p}{\partial x} - \frac{b(s,x)}{2}\frac{\partial^2 p}{\partial y^2}.$$

Suppose that a and b do not depend on time **Invariant density.**

$$\frac{\partial}{\partial y} \left[a(t,y) p(t,y) \right] = \frac{1}{2} \frac{\partial^2}{\partial y^2} \left[b(t,y) p(t,y) \right].$$

Generator. If f(t, x) is twice differentiable and the derivatives are bounded then

$$\lim_{h \to 0} \frac{E_{(t,x)}f(t+h, X_{t+h}) - f(t,x)}{h} = \frac{\partial f}{\partial t}(t,x) + a(x)\frac{\partial f}{\partial x}(t,x) + \frac{b(x)}{2}\frac{\partial^2 f}{Px^2}(t,x).$$

Martingales. $f(t, X_t)$ is a martingale iff

$$\frac{\partial f}{\partial t}(t,x) + a(x)\frac{\partial f}{\partial x}(t,x) + \frac{b(x)}{2}\frac{\partial^2 f}{Px^2}(t,x) = 0$$