



## MSML610: Advanced Machine Learning

# Stochastic Processes

**Instructor:** GP Saggese, PhD - [gsaggese@umd.edu](mailto:gsaggese@umd.edu)

**References:**

# Stochastic processes

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- Stochastic processes

# Random Variables and Index Sets

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- A stochastic process is a collection of random variables indexed by time or space
- Indexed set:  $\{X_t : t \in T\}$  where  $T$  can be discrete or continuous
- Describes evolving random phenomena
- Example: daily temperature, stock prices

# Markov Chains

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- Memoryless stochastic process:  $P(X_{t+1}|X_t, \dots, X_0) = P(X_{t+1}|X_t)$
- Characterized by a transition matrix  $P$
- Types: discrete-time, continuous-time
- Applications: web ranking, genetic modeling, board games

# Stationarity

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- A process is stationary if its statistical properties do not change over time
- Strict stationarity: joint distribution invariant under time shift
- Weak stationarity: constant mean and autocovariance depend only on lag
- Important in time-series modeling and signal processing

# Martingales

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- Process with conditional expectation:  $\mathbb{E}[X_{t+1}|X_1, \dots, X_t] = X_t$
- Models fair games and conservative estimates
- Used in financial modeling and online learning

# Poisson Process

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- Models arrival of random events in continuous time
- Events occur independently with constant average rate  $\lambda$
- Interarrival times are exponentially distributed
- Applications: queuing theory, rare event modeling

# Brownian Motion (Wiener Process)

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- Continuous-time stochastic process with stationary, independent Gaussian increments
- Starts at 0:  $B_0 = 0$
- Used in modeling diffusion, stock prices, reinforcement learning
- Foundation for stochastic differential equations



# Autoregressive (AR) Processes

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- $X_t$  depends linearly on its past values:  $X_t = \sum_{i=1}^p \phi_i X_{t-i} + \epsilon_t$
- $\epsilon_t$  is white noise
- Common in time-series forecasting (e.g., ARIMA)

# Moving Average (MA) Processes

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- $X_t$  is a linear function of current and past noise:  $X_t = \sum_{i=0}^q \theta_i \epsilon_{t-i}$
- Used to model short-term dependencies
- Often combined with AR in ARMA/ARIMA models

# Hidden Markov Models (HMMs)

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- Markov chain with unobserved (hidden) states
- Observations are generated from state-dependent distributions
- Used in speech recognition, bioinformatics, and NLP

# Gaussian Processes

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- A collection of random variables, any finite number of which are jointly Gaussian
- Fully specified by a mean function and covariance kernel
- Used in Bayesian regression, spatial modeling, and active learning

# Stochastic Differential Equations (SDEs)

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- Differential equations with random noise
- General form:  $dX_t = \mu(X_t, t)dt + \sigma(X_t, t)dB_t$
- Models continuous-time random phenomena
- Applications: physics, finance, control theory

# Ergodicity

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- Time averages equal ensemble averages under certain conditions
- Ensures statistical estimation is feasible from a single realization
- Crucial for learning from time-series data

# Renewal Processes

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- Generalization of Poisson processes
- Interarrival times are i.i.d. but not necessarily exponential
- Used in reliability theory and system maintenance

# Birth-Death Processes

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- Special case of Markov chains with transitions to neighboring states
- Models population dynamics, queue lengths
- Characterized by birth rate  $\lambda_n$  and death rate  $\mu_n$



# Queueing Models

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- Systems where entities wait in line for service
- Described using stochastic processes (e.g., M/M/1 queue)
- Analyzed via arrival and service rate distributions
- Applied in networks, servers, and traffic modeling

# Random Walks

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- Discrete stochastic process:  $X_{t+1} = X_t + \epsilon_t$
- $\epsilon_t$  is typically i.i.d. and symmetric
- Central to modeling cumulative processes and diffusion

# Time Series Analysis

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- Study of data indexed by time with inherent stochasticity
- Techniques: decomposition, smoothing, forecasting
- Used in econometrics, forecasting, and anomaly detection

# Law of Large Numbers and Central Limit Theorem

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- Justify convergence and Gaussian approximations of stochastic processes
- Law of large numbers: sample mean converges to expected value
- CLT: sum of i.i.d. variables approximates a normal distribution

# Monte Carlo Methods

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- Use stochastic sampling to approximate expectations and distributions
- Key for Bayesian inference and simulation
- Methods include importance sampling and MCMC

# Filtering and Prediction

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- Estimate current or future states from noisy observations
- Includes Kalman filters (linear-Gaussian) and particle filters (nonlinear)
- Essential in control, robotics, and state estimation