Machine Learning Course Notes (Weeks 0-12)

Week 0: Probability Theory, Linear Algebra, Convex Optimization

- - Probability Theory: Random variables (discrete/continuous), distributions (Bernoulli, Binomial, Poisson, Gaussian), expectation, variance, covariance, correlation, Bayes' theorem.
- - Linear Algebra: Vectors, matrices, linear independence, eigenvalues/eigenvectors, SVD.
- - Convex Optimization: Convex sets/functions, gradient descent, Lagrange multipliers.

Week 1: Statistical Decision Theory

- - Decision theory, loss function, risk, regression vs classification, bias-variance tradeoff.

Week 2: Linear Regression & Related Methods

- - Linear & multivariate regression, subset selection, ridge & lasso (shrinkage methods), PCR & PLS.

Week 3: Linear Classification

- - Logistic regression, linear discriminant analysis (LDA).

Week 4: Perceptron & SVM

- - Perceptron algorithm, weight update, support vector machines, kernels.

Week 5: Neural Networks

- - Neurons, layers, activation functions, backpropagation, initialization, training/validation, parameter estimation (MLE, MAP, Bayesian).

Week 6: Decision Trees

- - Regression/classification trees, splitting criteria, pruning, handling categorical/missing data, evaluation.

Week 7: Ensemble Methods

- - Bagging, boosting, stacking, random forests, evaluation metrics (accuracy, precision, recall, F1, ROC/AUC).

Week 8: Advanced Ensemble & Probabilistic Models

- - Gradient boosting, multi-class classification, Naive Bayes, Bayesian networks.

Week 9: Graphical Models

- - Undirected graphical models, HMM, inference (variable elimination, belief propagation).

Week 10: Clustering

- - Partitional (K-Means), hierarchical, BIRCH, CURE, density-based (DBSCAN).

Week 11: Gaussian Mixture Models & EM

- - GMM, EM algorithm (E-step & M-step).

Week 12: Learning Theory & Reinforcement Learning

- - PAC, VC dimension, RL concepts (agent, environment, reward, policy), TD learning, Q-learning, policy/value iteration.