Machine Learning Handbook

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Contents

Part I

High-level Views

Chapter 1

Math Review

1.1 Linear Algebra

Concepts:

- scalar, vector, matrix, tensor(n-rank tensor, matrix is a rank 2 tensor)
- Gaussian Elimination, rank
- p-norm
$$|X|_p = (\sum_i |x_i|^p)^{\frac{1}{p}}$$
- inner product$< x_i, y_i >$, outer product
- orthogonaldimension, basis, orthogonal basis
- linear transformation $Ax = y$
- eigenvalue, eigenvector $Ax = \lambda x$ (transformation and speed)
- vector space, linear space(with summation, scalar production), inner product space(inner product space)

1.2 Probability

Concepts:

- Classic Probability Model: Frequentist
- Bayesian Probability Theory
- Random variable, continuous RV, discrete RV, probability mass function, probability density function, cumulative density function
- Bernoulli distribution, Binomial distribution(n,p)

  $$P(X = k) = \binom{N}{k} p^k (1-p)^{(n-k)}$$

  , Poisson distribution

  $$P(X = k) = \lambda^k \frac{e^{-\lambda}}{k!}$$

- uniform distribution, exponential distribution

  $$e^{-\frac{x}{\theta}}\theta, P(x > s + t | X > s) = P(x > t)$$

  , normal distribution, t-distribution
- expectation, moments, variance, covariance, correlation coefficient

Theorems:

- Law of Total Probability
- Bayes' Rule

  $$P(H|D) = \frac{P(D|H)P(H)}{P(D)}$$

  P(H)-prior probability, P(D—H)-likelihood, P(H—D)-posterior probability,

1.2.1 Important Distributions, Moment Generating Functions

1. Normal Distribution, See next chapter
2. Bernoulli Distribution
3. Exponential Distribution $f_x(x, \theta) = \theta e^{-\theta x}$
4. Poisson Distribution

1.3 Information Theory

Concepts:

- Information
$$h(A) = -log_2 p(A)$$
(bit)
- (Information Source) Entropy
$$H(X) = -\sum_{i=1}^{n} p(a_i) log_2 p(a_i) \leq log_2 n$$
Maximize under equal probability
- Conditional Entropy
$$H(Y|X) = -\sum_{i=1}^{n} p(x_i) H(Y|X = x_i) = -\sum_{i=1}^{n} p(x_i) \sum_{j=1}^{n} p(y_j|x_i) log_2 p(y_j|x_i)$$
$$= \sum_{i=1}^{n} \sum_{j=1}^{n} p(x_i, y_j) log_2 p(y_j|x_i)$$
- Mutual Information/Information Gain
$$I(X;Y) = H(Y) - H(Y|X)$$

- Kullback-Leibler Divergence (K-L) Divergence

$$D_{KL}(P||Q) = \sum_{i=1}^{n} p(x_i) log_2 \frac{p(x_i)}{q(x_i)} \neq D_{KL}(Q||P)$$

$$D_{KL}(f, \hat{f})) = \int_{-\infty}^{\infty} log(\frac{f_X(x)}{\hat{f(x)}}) f_X(x) dx$$

  Measures the Distance of two distributions. The optimal encoding of information has the same bits as the entropy. Measures the extra bits if the real distribution is q rather than p. (Using P to approximate Q) K-L divergence plays an important role in both information theory and MLE theory. MLE $\hat{\theta}$ is actually finding the closest K-L Distance approximation of $f(x;\theta)$ to sample distribution.

Theorems:

- The Maximum Entropy Principle. Without extra assumption, max entropy/equal probability has the minimum prediction risk.

1.4 Optimization Theory

- Objective function/Evaluation function, constrained/unconstrained optimizationFeasible Set, Optimal Solution, Optimal Value, Binding Constraints, Shadow Price, Infeasible Price, Infeasibility, Unboundedness
- Linear Programming
- Lagrange Multiplier

$$L(x, y, \lambda) = f(x, y) + \lambda \varphi(x, y)$$

- Convex Set, Convex Function $f : S \to R$ is convex if and only if $\bigtriangledown^2 f(\mathbf{x})$ is positive semidefinite

Optimization Methods:

- Linear Search Method: Direction First, Step Size second
  - Gradient Descent: Batch Processing(Use all samples) vs Stochastic Gradient Descent(Use one sample)
  - Newton's Method: Use Curvature Information
- Trust Region: Step first, direction second. Find optimal direction of second-order approximation. If the descent size is too small, make step size smaller.
- Heuristics Method
  - Genetic Algorithm
  - Simulated Annealing
  - Partical Swarming/Ant Colony Algorithm

Theorems:

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1.5 Formal Logic

Concepts

- Generative Expert System: Rule+Facts+Deduction Engine
- Godel's incompleteness theorems

Chapter 2

Statistics

2.1 Concepts

2.1.1 Basic

- parameter(constant for probability model), statistic (model of sample data), data, sample, population
- point estimation, interval estimation, Confidence Interval($P(L \leq \theta \leq U)$, notice: θ is not random, L, U is random! (We repeat constructing confidence interval a n times, α percent of the times, it will contain $theta$.

2.1.2 Estimator and Estimation

- Method of Moments: $E(X^k)$ based on LOLN.
  If We have p parameters, we can use p moments to form a system of equations to solve $\theta_1, ...\theta_p$

  $$\sum_{i=1}^{n} X_i^j = E(X^j)$$

  , for j = 1,...,p
- Maximum Likelihood Estimation. Multiply p.m.f/p.d.f since every sample is independent. Maximize the likelihood of finding samples.

If $X_1, ...X_n \overset{i.i.d}{\sim} f_x(x, \theta)$,

$$l(\theta) = \prod_{i=1}^{n} f_{X_i} f_{x_i}(x_i; \theta), L(\theta) = logl(\theta)$$

$$\hat{\theta}_{MLE} = argmax_\theta f_x(x; \theta) = argmax_\theta L(\theta)$$

Analytical or Numerically solved.

$$\frac{\partial}{\partial\theta}[logL(\theta)] = 0, \frac{\partial^2}{\partial\theta^2}[logL(\theta)] < 0$$

, for multiple parameters, we need the Hessian matrix to be negative definite $x^t Hx < 0, \forall x$

- Properties of MLE
  1. Invariance $\hat{\theta}$ is MLE of θ, then $g(\hat{\theta})$ is MLE of $g(\theta)$
  2. Consistency
     $$P(\hat{\theta} - \theta) \to 0$$
     as $n \to 0, \forall\epsilon > 0$ Under the conditions
     (a) $X_1, ...X_n \overset{i.i.d}{\sim} f_x(x|\theta)$
     (b) parameters are identifiable, $\theta \neq \theta', f_x(x|\theta) \neq f_x(x|\theta')$
     (c) densities $f_x(x|\theta)$ has common support(set of x with positive density/probability), $f_x(x|\theta)$ is differentiable at θ
     (d) parameter space Ω contains open set ω where true θ_0 is an interior point
  3. Asymptotic Normality
     $$\sqrt{n}(\hat{\theta}_{MLE} - \theta_0) \to N(0, I^{-1}(\theta_0))$$
     $$I(\theta_0) = E(-(\frac{\partial}{\partial\theta}[logf(x, \theta)])^2) = E(-\frac{\partial^2}{\partial\theta^2}[logf(x, \theta)])$$
     called the Fisher Information
     $$\hat{\theta}_{MLE} \approx N(\theta_0, \frac{1}{nI(\theta_0)})$$
     $$nI(\theta_0) = E(-\frac{\partial^2}{\partial\theta^2}logL(\theta))$$

So the Variance of MLE($1/E(-\frac{\partial^2}{\partial\theta^2}logL(\theta))$) is the reciprocal of amount of curvature at MLE.
Usually, We can just use the *observed Fisher Information* (curvature near θ_{MLE}) instead. $(I(\theta_{MLE}))$
$\frac{1}{nI(\theta_0)}$ is called Cramer-Rao Lower Bound.
Under Multi-dimensional Case,

$$I(\theta_0)_{ij} == E(-\frac{\partial^2}{\partial\theta_i\partial\theta_j}[logf(x,\theta)])$$

$Hessian \approx nI(\theta_0)$ $Hessian^{-1} \approx nI(\theta_0)$ when we use numerical approach.

Under the above four conditions plus

(a) $\forall x \in \chi$, $f_x(x|\theta)$ is three times differentiable with respect to θ, and third derivative is continuous at θ, and $\int f_x(x|\theta)dx$ can be differentiated three times under integral sign

(b) $\forall\theta \in \Omega, \exists c, M(x)$ (both depends on θ_0) such that

$$\frac{\partial^3}{\partial\theta^3}[logf(x,\theta)] \leq M(x), \forall x \in \chi, \theta_0 - c < \theta < \theta_0 + c, E_{\theta_0}[M(x)] < \infty$$

- Δ -Method: $g(th\hat{e}ta_{MLE})$ is approximately

$$N(g(\theta), (g'(\theta))^2\frac{1}{nI(\theta)})$$

if asymptotic normality is satisfied.
In Multivariate Case:

$$\hat{\theta} \sim N(\theta, \Sigma/n), \theta, \hat{\theta} \in R^p$$

$$g : R^p \to R^m$$

$$g(\hat{\theta}) \sim N(g(\theta), G\Sigma G^T/n)$$

$$G = \begin{pmatrix} \frac{\partial g_1(\theta)}{\partial\theta_1} & \dots & \frac{\partial g_1(\theta)}{\partial\theta_p} \\ \vdots & \ddots & \vdots \\ \frac{\partial g_m(\theta)}{\partial\theta_1} & \dots & \frac{\partial g_m(\theta)}{\partial\theta_p} \end{pmatrix}$$

- Estimation criteria
  - Unbiased $E(\hat{\theta}) = \theta$

- Minimum Variance (MVUE, minimum variance unbiased estimator) $Var(\hat{\theta}) < Var(\theta')$
- Efficient
- Coherent

2.1.3 Model Selection

AIC - Akaike Information Criterion

By K-L Distance

$$D_{KL}(f, \hat{f})) = \int_{-\infty}^{\infty} log(\frac{f_X(x)}{f(\hat{x})}) f_X(x) dx$$

$$= const + \frac{1}{2} \int (-2log\hat{f}(x)) f(x) dx = const + AIC$$

$$A(f, \hat{f}) = -2logL(\theta) + 2p(\frac{n}{n-p+1})$$

2.1.4 Hypothesis Testing

- Hypothese, Test Statistic(T), Rejection Region
- p-value (chance of rejecting, largest choice of α that we would fail to reject H_0)
- type-I error(wrongly reject), type-II error(wrongly accept)

Hypothesis Testings (Based on the distribution of $\hat{\theta}$)

- Wald Test

$$T = \frac{\hat{\theta} - \theta_0}{Se(\hat{\theta})}$$

$$\hat{\theta}_{MLE} \approx N(\theta_0, \frac{1}{nI(\theta_0)})$$

$$T = \frac{\hat{\theta} - \theta_0}{\sqrt{\frac{1}{nI(\theta_0)})}}$$

- Likelihood Ratio Test
- Score Test

*Computation-based hypothesis testing approach

- Permutation tests:
  Test $X_1, ..X_n \sim F, Y_1, ...Y_n \sim G, if F = G$. Use
  $T = Mean(X_i) - Mean(Y_i)$, each time scramble X and V labels and should not not change the distributions of vectors $X_1, ...X_n, Y_1..., Y_n$
- Bootstrapping:
  $X_1, ...X_n \sim F$ with $T = T(X_1, ..., X_n)$, to get the distribution of T, **sample with replacement.** The belief is $(\hat{\theta} - \theta)$ should behave the same as $(\theta * -th\hat{e}ta)$. The first quantity can be treated like a pivot. (use $(\theta *_1 -\hat{\theta}_1), ...(\theta *_n -\hat{\theta}_n)$ to test.

Multiple Testing

- Family-wise Error Rate(FWER) the probability of rejecting at least one of at least one null hypothesis
  Under independence, the probability of making mistake when all null are true: (P(any type I mistake) = 1-P(no type I mistake for all) = $1 - (1 - \alpha)^M = \beta$)
- Bonferroni correction, assuming independence
  $P(\bigcup_{i=1}^n typeI_mistake) \leq \sum_{i=1}^n P(typeI_mistake) \leq M\alpha$, control at $\alpha = \frac{\alpha}{M}$
  α being to small will impact power of the individual tests!
- False Discovery Rate(FDR): bound the fraction of type-I errors. R be the total number of hypotheses rejected. V be the number of rejected hypotheses that were actually null. Let FDR = V/max(R,1), control $E(FDR) \leq \alpha$.

2.2 Theorems

- Law of Large Number

- Central Limit Theorem
- Bias/Variance decomposition (error = bias + variance + noise)

$$MSE(\mu(X)) = E[(Y - \hat{\mu}(X))^2] == E[(Y - f(x) + f(x) - \hat{\mu}(X))^2]$$
$$= E[(Y - f(x)]^2 + 2E[(Y - f(x))(f(x) - \hat{\mu}(X))] + E[(f(x) - \hat{\mu}(X))^2]$$
$$= E[(Y - f(x)]^2 + 2E[(Y - f(x))(f(x) - \hat{\mu}(X))] + (f(x) - \hat{\mu}(X))^2$$
$$= \sigma_x^2 + Bias(\hat{\mu}(X))^2 + Var(\hat{\mu}(X))$$

2.3 Important Distributions

1. Normal Distribution, $X_1, ...X_n \sim N(\mu, \sigma^2)$ then
   (a) $\bar{X}$ and s^2 are independent
   (b) $\frac{\bar{X}-\mu}{\sigma/\sqrt{n}} \sim N(0,1)$
   (c) $\frac{(n-1)s^2}{\sigma^2} \sim \chi^2_{n-1}$
   (d) $\frac{\bar{X}-\mu}{s/\sqrt{n}} = \frac{\frac{\bar{X}-\mu}{\sigma/\sqrt{n}}}{\frac{(n-1)s^2}{\sigma^2}\frac{1}{\sqrt{n-1}}} \sim t_{n-1}$
2. Multi-variate normal distribution

$$f_x(x) = \frac{1}{(2\pi)^{p/2}|\Sigma|^{1/2}} exp(-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu))$$

   (a) $X_1, ...X_n$ normal $\Leftarrow (X_1, ...X_n)$ is multivariate normal. (Not equivalent)
   (b) $E(X) = \mu, Var(X) = \Sigma$
   (c) Linear transformations $AX + b \sim N(A\mu + b, A\Sigma A^T)$ remain multivariate normal
   (d) Marginals are multivariate normal, each sub-vector is multivariate normal, the parameters are just sub-matrices.
   (e) All conditionals are multivariate normal
3. t-distribution: like normal distribution, but heavier tails
   (a) $Z \sim N(0,1), Y \sim \chi^2_\nu$, Z, Y independent,

$$X = Z/\sqrt{Y/\nu} \sim t_\nu$$

(b) pdf has polynomial tails (decays much slower than exponential ones)

(c) $\nu = 1$, it is the **Cauchy Distribution**, with very heavy tails (no expectation)

(d) The MCF not exist. $E(|X|^k) < \infty$ for $k < \nu$, $E(|X|^k) = \infty$ for $k > \nu$

(e) $X \sim t_\nu, E(X) = 0, Var(X) = \frac{\nu}{\nu-2}$

$$f_X(x) = \frac{1}{\pi(1+x^2)}$$

4. χ^2 distribution

$$f_x(x) = \frac{1}{(2^{k/2}\Gamma(k/2)}x^{\frac{k}{2}-1}e^{-\frac{x}{2}}, x \in [0,\infty) \sim Gamma(\frac{k}{2}, \frac{1}{2})$$

(a) $E(X) = k, Var(X) = 2k, M_X(t) = (\frac{1}{1-2^t})^{k/2}$

(b) $X \sim N(0,1) \Rightarrow X^2 \sim \chi^2$, $X_1, ...X_n \sim N(0,1) i.i.d \Rightarrow \sum X_i^2 \sim \chi^2$,

$$f_X(x) = \frac{1}{\pi(1+x^2)}$$

More Generalized Distributions

1. Generalized Error Distribution (symmetric)
2. Non-standard t-distribution (shift and scaling, heavy tailed, symmetric)
3. Theodossious skewed t-distribution
4. Theodossious skewed t-distribution plus shift

2.4 Practice/Examples

1. sample mean($\bar{X}$) is unbiased. Sample variance $(\frac{1}{n-1}\sum_{i=1}^n x_i^n)$ is unbiased. But sample std is not unbiased. $SE(\bar{X}) = \frac{\sigma^2}{n}$
2. $\hat{Cov}(X.Y) = \frac{1}{n-1}\sum_{i=1}^n (X_i - \bar{X})(X_i - \bar{Y})$ is unbiased

3. Distributions with Expectation not exist? (Cauchy)

4. Common Confidence Intervals:
μ: $P(-t_{\alpha/2,n-1} \leq \frac{\bar{X}-\mu}{s/\sqrt{n}} \leq t_{\alpha/2,n-1}) = 1-\alpha$,
σ: $P(a \leq \frac{(n-1)s^2}{\sigma^2} \leq b) = 1-\alpha$

5. Solve MLE/MOM for beta, exponential $(n/\sum X_i$, normal

6. * prove Asymptotic Normality of MLE(hint: using Taylor Expansion for $\theta, \hat{\theta}$)

7. * Use t^{th} quantile to approximate c.d.f, what's the distribution? $(Y_n = \frac{1}{n}\sum I(X_i < x)$, a Bernoulli distribution with $p = F_x(x)$, $\sqrt{n}[Y_n(x) - F_x(x)] \sim N(0, F(x)(1-F(x))$.

8. $X_1, ...X_n \sim Binomial(n,p)$, What's the MLE for p and Fisher Information? ($\hat{p} = \frac{x_i}{n}, I(p) = 1/p(1-p), var(p) = \frac{p(1-p)}{n}$)

9. $(x_i, y_i) \sim N(\mu_i, \sigma^2)$, find MLE for σ ($\frac{1}{4N}\sum(x_i - y_i)$)

10. How can you get N(0,1) random variables from U[0,1]? (Method1: Inverse Transformation, Method2; Use
$SumZ_i^2 \sim \chi_k^2, k = 2, F^{-1}(u) = -2log(1-u)$,
$R^2 \sim \chi^2, Z_1 = Rcos\theta, Z_2 = Rsin\theta, \theta \in [0, 2\pi]$

11. (Permutation test) how can you test $X_1, ..., X_n \sim F$, how can you test if F is symmetric? (Multiply -1 on all two form two sample groups)

12. Draw a bootstrap sample, what fraction of original data points appear in this sample on average?
Define I be the indicator is it is in the sample.
$E(\frac{1}{n}\sum I_i = E(I_i) = P(\text{ith point shows up}) = 1 - (1-\frac{1}{n})^n$

Chapter 3

Bayesian Statistical Theory

Bayes' Rule

$$f_{Y|X}(y|x) = \frac{f_{(X,Y)}(x,y)}{f_X(x)} = \frac{f_{(X,Y)}(x,y)}{\int f(x|y)f(y)dy}$$

Byesian Inference:
All parameters are random variables,

$$\pi(\theta|x) = \frac{f(x|\theta)\pi(\theta)}{\int f(x|\theta)\pi(\theta)d\theta}$$

$$\pi(\theta|x) \sim f(x|\theta)\pi(\theta)$$

$\pi(\theta)$ is the prior distribution, $\pi(\theta|x)$ is the posterior distribution for θ given x.

Bayes Estimator

$$\hat{\theta}_{Bayes} = E(\theta|X) = \int \theta\pi(\theta|X)d\theta$$

Conjugate Distribution: $f(x), \pi$ is called conjugate distributions if model $\pi(\theta|x), \pi(\theta)$ follows the same Distribution

eg. Bernoulli(θ) and Beta(α, β), ($\pi(\theta|x) \sim$ Beta($\alpha + \sum X_i, \beta + n - \sum X_i$)
($f(x|\theta) = \prod_{i=1}^n f_{X_i}(X_i|\theta)$)

$$\hat{\theta}_{Bayes} = E(\theta|X) = \frac{\alpha + \sum X_i}{\alpha + \beta + n}$$

$$= \frac{\sum X_i}{n} \frac{n}{\alpha+\beta+n} + \frac{\alpha}{\alpha+\beta} \frac{\alpha+\beta}{\alpha+\beta+n}$$

The prior mean (second term) influences less as n grows.

Poisson(θ) and $Gamma(\alpha + \sum X_i, \beta + n)$

3.1 Bayesian Decision Theory

In State ω we take action $a \in A$, incurr Loss $L(\omega, a)$, how to choose a?
Risk:

$$R(a|x) = \sum_{j=1}^{k} L(\omega_j, a) P(\omega_j|x)$$

Decision Rule $d \in A$

$$d^*(x) = \arg\min_{a \in A} R(a|x)$$

Chapter 4

Computational Learning Theory

Part II

Supervised Learning Models

Chapter 5

Regression Overview and Linear Regression

5.1 Overview

All Basic Models begins with **Linear Regression** Because

- Linear relationship is the simplest relationship other than constant relationship or "null" model (average)
- It's a global model
- Data Invariance: Simple linear model don't do any pre-processing or transformation on the covariants.
- Very Explainable, limited interpretation power.

So, the alternation/improvements also focuses on these aspects

- Nonlinear features-Introduction of basis function
  - Polynomial Regression
  - Spline Models(eg. Cubic Spline, Smoothing Spline)

- Nonlinear parameters: Parameters Self-adjusting.(activation function is an example of basis function as well)
  - Neutral-Network
- global nonlinear: global nonlinear on both parameters and features achieved by linkage function, extends regression models to classification.
  - Generalized Linear Model
- Change the global model to a local model
  - Local Regression (Regression + KNN)
  - Nonparametric Regression
  - Kernel Function
  - Distance Based Learning
- Data Preprocessing (Transformation) and Dimension Reduction
  - PCA
  - LDA
  - Manifold Learning
- Improve Generalization Capability from outside (not from inside the model)
  - Regularization Methods(eg. Ridge, Lasso)
  - Ensemble Learning(Stacking, Aggregating): Random Forest, Boosting(GBDT), Deep Learning...

5.2 Linear Regressions

Common Terms

1. Independent Variable=Features=covariates
2. Dependent Variable=

5.2.1 Assumptions

Classic Assumptions for Statistics:

1. Linear Relationship between covariates and dependent variable
2. $E(\varepsilon) = 0$
3. $Var(\varepsilon) = \sigma^2$: Homoscedasticity
4. ε is independent with covariates
5. x is observed without error
6. (optional, Gauss-Markov Theorm) ε is normal - when it is, OLS and MLE agrees and to be BLUE(Best Linear Unbiased Estimator)

5.2.2 Intepretaion

Under Normal Condition, we have

$$y \sim N(\beta_0 + \beta x_i, \sigma^2), L(\theta) = (\frac{1}{\sqrt{2\pi\sigma)}}^n exp(-\frac{\sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_i))^2}{2\sigma^2})$$

Equivalent to minimize

$$RSS(\theta) = \sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_i))^2$$

$$\partial_{\beta_i} RSS = 0, i = 1, 2$$

, we get

$$r_{xy} = \frac{s_{xy}}{s_x s_y}, \beta_1 = r_{xy}\frac{s_y}{s_x} = \frac{s_{xy}}{s_x^2}, \beta_0 = \bar{y} - \hat{\beta}\bar{x}$$

In Multi-variate Case:

$$f(x) = \mathbf{w}^T \mathbf{x} = \sum_{i=1}^n w_i x_i$$

$$\mathbf{w}* = (\mathbf{X^T X})^{-1}\mathbf{X^T y}$$

RSS Approach:

MLE Approach

Assuming noise is normal, maximize

$$p(\mathbf{x_1}, \mathbf{x_2} ... \mathbf{x_n} | \mathbf{w}) = \prod_k \frac{1}{\sqrt{2\pi}\sigma} exp[-\frac{1}{2\sigma^2}(y_k - \mathbf{w_t x_k})^2]$$

5.2.3 Lasso-Least Absolute Shrinkage and Selection Operator

$$min||y_k - \mathbf{w^T x}_k||^2 + \lambda||\mathbf{w}||_1$$

5.3 Regularization, Ridge and Lasso

Chapter 6

Logistic Regression and Generalized Linear Model

Chapter 7

Neutral-Network

Chapter 8

Distance and Kth Nearest Neighbors

Chapter 9

Naive Bayesian

Chapter 10

Tree Models and Ensemble Learning

Stacking Aggregating: Random Forest, Boosting(GBDT), Deep Learning...

Part III

Unsupervised Learning Models

Chapter 11

Clustering

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12.1 PCA

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Part IV

Deep Learning and Enhanced Learning Theory

Chapter 13

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