

Machine Learning – Key Concepts & Formula Sheet

For BITS AIML CZG565 (Exam-Oriented Summary)

Module 1: Introduction to Machine Learning

- Learning task defined by ■ Task (T), Performance (P), Experience (E)■
- Supervised, Unsupervised, Semi-supervised, Reinforcement Learning
- Classification → categorical output, Regression → continuous output
- Generative models learn $P(x,y)$; Discriminative models learn $P(y|x)$

Module 2: ML Workflow & Data Preprocessing

- Workflow: Problem → Data → Cleaning → Features → Model → Train → Evaluate
- Data issues: Missing values, noise, outliers, duplicates
- IQR = $Q3 - Q1$; Outliers if $x < Q1 - 1.5 \times IQR$ or $x > Q3 + 1.5 \times IQR$
- 3-Sigma Rule: $\mu \pm 3\sigma$
- Min-Max: $(x - x_{min}) / (x_{max} - x_{min})$
- Z-score: $(x - \mu) / \sigma$

Module 3: Linear Regression

- Model: ■ = $w_0 + w_1x_1 + \dots + w_nx_n$
- MSE Cost: $J = (1/n) \sum (\text{■} - y)^2$
- Gradient Descent: $w_j = w_j - \alpha(\partial J / \partial w_j)$
- Normal Equation: $w = (X \text{■} X)^{-1} X \text{■} y$
- $R^2 = 1 - SS_{res} / SS_{tot}$

Regularization

- Ridge (L2): $J = \text{MSE} + \lambda \sum w_j^2$
 $\partial J / \partial w_j = (1/n) \sum (\text{■} - y)x_j + (\lambda/n)w_j$
- Lasso (L1): $J = \text{MSE} + \lambda \sum |w_j|$
 $\partial J / \partial w_j = (1/n) \sum (\text{■} - y)x_j + (\lambda/n) \text{sign}(w_j)$

Module 4: Logistic Regression

- Sigmoid: $\sigma(z) = 1 / (1 + e^{\text{■}})$
- Model: $h(x) = \sigma(w \text{■} x)$
- Cross-Entropy Cost:
 $J = -(1/n) \sum [y \log(h) + (1-y) \log(1-h)]$
- Decision rule: $h(x) \geq 0.5 \rightarrow \text{class 1}$
- $\text{logit}(p) = \log(p/(1-p)) = w \text{■} x$
- Accuracy = $(TP+TN)/\text{Total}$
- Precision = $TP/(TP+FP)$
- Recall (TPR) = $TP/(TP+FN)$
- FPR = $FP/(FP+TN)$
- ROC curve plots TPR vs FPR; AUC=1 perfect, 0.5 random

Module 5: Decision Trees

- Entropy: $H(S) = -\sum p_i \log \text{■} p_i$
- Information Gain: $\text{Gain}(S,A) = \text{Entropy}(S) - \sum (|S_v|/|S|) \text{Entropy}(S_v)$
- Gini Index: $1 - \sum p_i^2$
- Gain Ratio = $\text{Gain} / \text{SplitInfo}$

- Stop when node is pure, no attributes left, or gain is small
- Overfitting control: prepruning, postpruning, depth limits