Math 342W Lecture 20

Information on Models (Types)

Response Space	Model Type	g returns	$\mathcal{A}$	Estimates
$y \subseteq \mathbb{R}$	Regression	$\hat{y} \in \mathbb{R}$	OLS	y
$y = \{C_1, C_2, \ldots, C_L\}$	Classification	$\hat{y} \in \{C_1, \ldots, C_L\}$	KNN	y
$y = \{0, 1\}$	Binary Classification	$\hat{y} \in \{0, 1\}$	SVM	y
$y = (0, 1)$	Proportion	$\hat{y} \in (0, 1)$	Beta Regression	y
$y = \mathbb{R}_{\geq 0}$	Survival	$\hat{y} \in \mathbb{R}_{\geq 0}$	Weibull Regression	y
$y = \{0, 1, 2, \ldots\}$	Count	$\hat{y} \in \{0, 1, 2 \ldots\}$	Poisson Regression	y
$y = \{0, 1\}$	Probability Estimation Model	$\hat{p} \in [0, 1]$	Logistic Regression	$P(Y=1) = \hat{p}$
$y = \{C_1, \ldots, C_L\}$	" "	$\hat{p} \in [0, 1]^L$	Multi-Logit Regression	$\begin{bmatrix} P(Y=C_1) \\ \vdots \\ P(Y=C_L) \end{bmatrix}$
$y = \{C_1, \ldots, C_L\}$	" "	" "	Proportional Odds Model	" "

ordinal

These are some of the types of models in existence, but some of the more frequently used types.

Asymmetic Cost Modeling

Traditional Misclassification Error $= \frac{1}{n} \underbrace{\sum_{i=1}^{n} \mathbb{1}_{\hat{y}_i \neq y_i}}_{e_i \neq 0} \Rightarrow e_i = y_i - \hat{y}_i$

		$\hat{y}$: 0	1
y	0	0	-1
	1	+1	0

False Positive

False Negative

Misclassification Error $= \frac{\sum_i (fp + fn)}{n}$

Another Objective Function $\Rightarrow$ TotalCost $= C_{FP} \cdot FP + C_{FN} \cdot FN$

↳ Averge Cost = TotalCost / n

A: Minimize Total Cost $\Rightarrow$ Asymetric Cost Model $(C_{FP} \neq C_{FN})$

$y = \{0,1\} \iff Y \sim Bern(t(\vec{z})) \Rightarrow Y \sim Bern(f_{pr}(\vec{x}) + (t(\vec{z}) - f_{pr}(\vec{x})))$

$y = t(\vec{z})$ | $\Rightarrow Y \sim Bern(f_{pr}(\vec{x}))$

$= f(\vec{x}) + \delta$, $\delta \in \{-1,0,1\}$ | $\Rightarrow Y \sim Bern(h^*_{pr}(\vec{x}) + (f_{pr}(\vec{x}) - h^*_{pr}(\vec{x})) + (t(\vec{z}) - f_{pr}(\vec{x})))$

$= h^*(\vec{x}) + \mathcal{E}$, $\mathcal{E} \in \{-1,0,1\}$ | $\Rightarrow Y \sim Bern(g_{pr}(\vec{x}) + \ldots)$

$= g(\vec{x}) + e$, $e \in \{-1,0,1\}$ | $\Rightarrow Y \sim Bern(g_{pr}(\vec{x})) \Rightarrow \hat{p} = g_{pr}(\vec{x})$, estimating $P(Y=1 \mid \vec{x})$

Shows "$\mathcal{E}$"

$f_{pr}(\vec{x}) : \mathbb{R}^p \to (0,1)$

$h^*_{pr}(\vec{x}) : \mathbb{R}^p \to (0,1)$

$g^*_{pr}(\vec{x}) : \mathbb{R}^p \to (0,1)$