

R_{MSE} vs R^2 — who is more important for assessing predictive ability? R_{MSE} (usually) why?

R_{MSE} answers the question: how good are my predictions? what is the std err of my predictions?

$$R^2 \uparrow \Rightarrow R_{MSE} \downarrow$$

$$R^2 \downarrow \Rightarrow R_{MSE} \uparrow$$



$R^2 = 99\%$ How can this be bad?



Bad!!

If $R^2 = 99\%$, could R_{MSE} still be big? Yes. Maybe there was a ton of variance in y , you explained most of it, but there is still a lot left...

$R_{MSE} \approx s_e$ (a constant std dev. in residuals)

Empirical Rule

$$\hat{y} \pm 2 \cdot s_e \approx 95\% \text{ of all predictions (if } E \sim N(0, \sigma^2))$$

$$\hat{y} \pm 3 \cdot s_e \approx 99.7\% \text{ of all predictions (if } E \sim N(0, \sigma^2))$$

What if you're doing regression i.e. $y \in \mathbb{R}$ at $p=1$ but the feature is a factor with two levels.

$X \in \mathcal{X} = \{\text{Red, Green}\}$ How to model? Try linear model

let red $\rightarrow 0$, green $\rightarrow 1$ and create a binary variable $\tilde{x} \in \{0, 1\}$.

What would the hyp. set look like?

$$\mathcal{H} = \{w_0 + w_1 \tilde{x} : w_0 \in \mathbb{R}, w_1 \in \mathbb{R}\} = \{w_0 + w_1 \mathbb{1}_{X=\text{Green}} : w_0 \in \mathbb{R}, w_1 \in \mathbb{R}\}$$

so the final model $\hat{y} = b_0 + b_1 \tilde{x} = b_0 + b_1 \mathbb{1}_{X=\text{green}}$

You can fit this with least squares. What do you think the answer will be?

$$\hat{y} = \begin{cases} \bar{y}_{\text{red}} & \text{if } x = \text{red} \\ \bar{y}_{\text{green}} & \text{if } x = \text{green} \end{cases} = \underbrace{\bar{y}_{\text{red}}}_{b_0} + \underbrace{(\bar{y}_{\text{green}} - \bar{y}_{\text{red}})}_{b_1} \mathbb{1}_{x = \text{green}}$$

red is called the ref. level / category.
 b_1 represents the added effect of green over red.

Let's see if we can prove this. Let

$$p = \frac{\sum \mathbb{1}_{x_i = \text{green}}}{n} \quad \text{i.e. prop of green}$$

$$(1-p) = \text{prop of red}$$

$$b_0 = \bar{y} - b_1 \bar{x}$$

$$\text{Assume } b_1 = \bar{y}_g - \bar{y}_r$$

$$\bar{y} = \frac{y_1 + \dots + y_n}{n} = \frac{\overbrace{y_1 \dots y_{n_g}}^{\text{green}}}{n} + \frac{\overbrace{y_{n_g+1} \dots y_n}^{\text{red}}}{n} = \frac{\bar{y}_g n_g}{n} + \frac{\bar{y}_r n_r}{n} = p \bar{y}_g + (1-p) \bar{y}_r$$

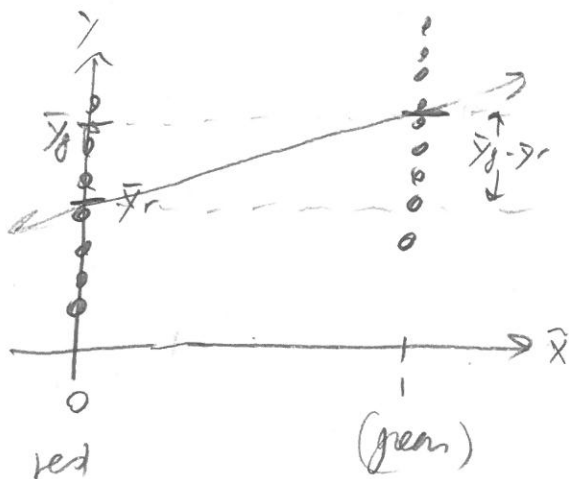
$$\bar{x} = p$$

$$\Rightarrow b_0 = p \bar{y}_g + (1-p) \bar{y}_r - p(\bar{y}_g - \bar{y}_r) = (1-p) \bar{y}_r + p \bar{y}_r = \bar{y}_r \quad \checkmark$$

$$b_1 = \frac{\sum x_i y_i - n \bar{x} \bar{y}}{\sum x_i^2 - n \bar{x}^2} = \frac{\sum_{\text{green}} (1) y_i + \sum_{\text{red}} (0) y_i - n \bar{p} \bar{y}}{\sum_{\text{green}} 1^2 + \sum_{\text{red}} 0^2 - n p^2} = \frac{n_g \bar{y}_g - n p \bar{y}}{n_g - n p^2}$$

$$= \frac{\bar{y}_g - \bar{y}}{1-p} = \frac{\bar{y}_g - (p \bar{y}_g + (1-p) \bar{y}_r)}{1-p} = \frac{(1-p) \bar{y}_g - (1-p) \bar{y}_r}{1-p} = \bar{y}_g - \bar{y}_r \quad \checkmark$$

What does this look like?



What if there were more than 2 levels in the factor?

$$x \in \{\text{red}, \text{green}, \text{blue}\}$$

Recall our idea from early in the class:

$$x \Rightarrow \{\tilde{x}_1, \tilde{x}_2, \tilde{x}_3\} \quad \text{one variable becomes 3 dummy variables (i.e. "dummyification")}$$

$$x_1 = \mathbb{1}_{x=\text{red}}$$

$$x_2 = \mathbb{1}_{x=\text{green}}$$

$$x_3 = \mathbb{1}_{x=\text{blue}}$$

Can we fit a model on $y \sim x$. No, not without dummying.

This leads us into "multivariate regression".

Let's remind ourselves of the modeling step:

Let's say we have D with p features and normally we could fit a model.

$$\mathcal{H} = \{w_0 + w_1 x_1 + \dots + w_p x_p : w_0 \in \mathbb{R}, w_1 \in \mathbb{R}, \dots, w_p \in \mathbb{R}\}$$

$$= \{\vec{w} \cdot \vec{x} : \vec{w} \in \mathbb{R}^{p+1}\} \quad \text{line } \vec{x} = [1 \ x_1 \ \dots \ x_p]$$

Let's choose some R , ordinary least squares:

$$SSE = \sum_{i=1}^n e_i^2 = \sum (y_i - \hat{y}_i)^2 = \sum (y_i - (w_0 + w_1 x_{i1} + \dots + w_p x_{ip}))^2$$

argmin SSE

$w_0 \in \mathbb{R}$
 $w_1 \in \mathbb{R}$
 \vdots
 $w_p \in \mathbb{R}$

\Rightarrow highdimension

Need better way

MIDTERM 1

MIDTERM 2