

Lab: Simple Linear Regression

1. Pythagorean Win Percentage

We are given a dataset of team-seasons from 2017 to 2021,

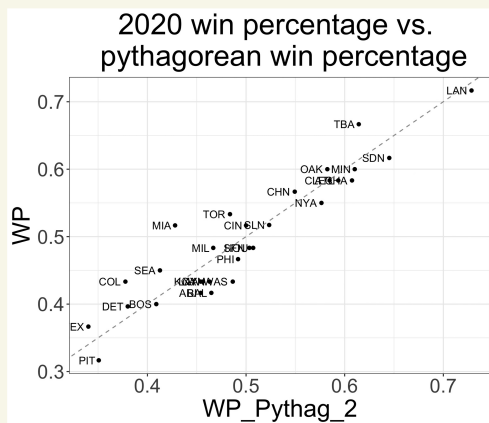
$$\begin{cases} i = \text{index of } i^{\text{th}} \text{ team-season} \\ RS_i = \text{runs scored} \\ RA_i = \text{runs allowed} \\ WP_i = \text{win percentage} \end{cases}$$

and we want to predict end-of-season win percentage from runs scored and runs allowed. A team's deviation from this prediction is a measure of how lucky the team was.

Bill James, godfather of Sabermetrics (baseball analytics) and sports analytics, created Pythagorean Win Percentage

$$\widehat{WP} = \frac{RS^2}{RS^2 + RA^2}$$

He made it up and it works quite well!



The pythagorean exponent is quite good, but is arbitrary.

- Use linear regression to find an exponent α so that the pythagorean win percentage

$$\widehat{WP} = \frac{RS^\alpha}{RS^\alpha + RA^\alpha} \text{ best fits the data.}$$

You'll need to transform this equation to be linear in α .

Hint: divide top and bottom by RS^α

- Create a visualization to show that

$$\widehat{WP} = \frac{RS^{\hat{\alpha}}}{RS^{\hat{\alpha}} + RA^{\hat{\alpha}}} \text{ is better than } \widehat{WP} = \frac{RS^2}{RS^2 + RA^2}.$$

2. Evaluating MLB general managers

We are given a dataset of MLB team payrolls and results for each season 1998-2023,

$$\left\{ \begin{array}{l} \text{row } i \leftarrow i^{\text{th}} \text{ team-season} \\ \text{win percentage} \\ \text{payroll/median payroll} \\ \text{Log}(\text{payroll/median payroll}) \end{array} \right.$$

We want to analyze the relationship between payroll and winning to evaluate general managers.

(Try using Chat GPT Data Analyst for this question)

- Plot payroll/median against winning percentage, mark the Oakland A's and NY Yankees dots.

Remove 2020.

Add the regression line of WP as a function of payroll/median. Add the regression line of WP as a function of $\log(\text{payroll/median})$.

● Now for each team-season calculate the difference between the actual WP and predicted WP using payroll/median and then $\log(\text{payroll}/\text{median})$. Add this column to the dataset.

Find the average difference for each team and make a graph ordered from highest to lowest. (one graph for each model).

Change the y axis scale to wins by multiply by 162.

● Note :

Let $x = \text{payroll} / \text{median}$

Model A: $WP = \alpha_0 + \alpha_1 \cdot x + \varepsilon$

Model B: $WP = \beta_0 + \beta_1 \cdot \log(x) + \varepsilon$

● Interpretation of Model A:

increasing x by a constant value of 1 median payroll adds $\hat{\alpha}_1$ to \widehat{WP}

● Interpretation of Model B:

increasing x by $r \times 100\%$ adds $\hat{\beta}_1$ to \widehat{WP}

Proof

$x' = (1+r)x$ increase x by $r \cdot 100\%$

then $\widehat{WP}' = \beta_0 + \beta_1 \log(x')$

$$= \beta_0 + \beta_1 \log[(1+r)x]$$

$$= \beta_0 + \beta_1 \log(1+r) + \beta_1 \log(x)$$

$$\approx \beta_0 + \beta_1 \log(x) + \beta_1 \cdot r$$

since for r small, $\log(1+r) \approx r$

$$= \widehat{WP} + \beta_1 \cdot r$$

Which model is better intuitively?