

Modeling Task $f = f(I, R)$

* Statistical Models vs. Mathematical Models (Machine Learning)

- Statistical/Machine Learning Models are fit from historical data
- Mathematical Models are equations written on paper

Models fit from historical data

- What data do we need?
Can we get it?
Get it.
- Choose the model

Mathematical Models

- What Random variables / distribution

Are appropriate, if any?

- Statistical/Machine Learning Models
are fit from historical data

Models fit from historical data

- What data do we need?
Can we get it?
get it.
- Choose the model

$$f = f(I, R) = \text{Starting pit allows } R \text{ runs through } I \text{ innings, win prob.}$$

data

every starting-pitcher-game \rightarrow index $i = 1, \dots, n$

R_i = runs allowed by S.p. in game i

I_i = innings pitched by S.p. in game i

(for simplicity assume S.p. pulled after fully completing I_i)

$y_i = 1$ if S.p. team wins, else 0

Lahman \rightarrow box score

Retrosheet/Stotz \rightarrow PBP

Empirical grid

$$\hat{f}(I, R) = \text{Mean} \{ y_i : I = I_i \text{ and } R = R_i \}$$

(I, R)

$$(4, 2) \quad \frac{70}{308} \begin{matrix} \text{Win} \\ \text{Loss} \end{matrix} \approx 0.7$$

XGBoost with Monotonic Constraints

XGBoost = one of the fastest and easiest to use "off-the-shelf" machine learning algorithms, supervised

dependent variables X_1, \dots, X_p
independent variables y

XGBoost "memorizes" as best as possible
 $g(x) = y \rightarrow$ interpolates

Monotonic constraints:

$R \rightarrow$ tell X_{first}^R to be ^{monotonic} decreasing in R

$I \rightarrow$ tell X_{first}^I to be monotonic increasing in I

Try Mathematical Models

$(R, I) \rightarrow$ win probability

say inning i $X_i =$ # runs scored by team \spadesuit ^{the pitcher's}
 $Y_i =$ # runs scored by ^{the opp's} team \clubsuit

$$\begin{aligned}\hat{f}(I, R) &= P\left(\sum_{i=1}^q X_i > R + \sum_{i=I+1}^q Y_i\right) \\ &+ \frac{1}{2} P\left(\sum_{i=1}^q X_i = R + \sum_{i=I+1}^q Y_i\right)\end{aligned}$$

Start simple \rightarrow Poisson

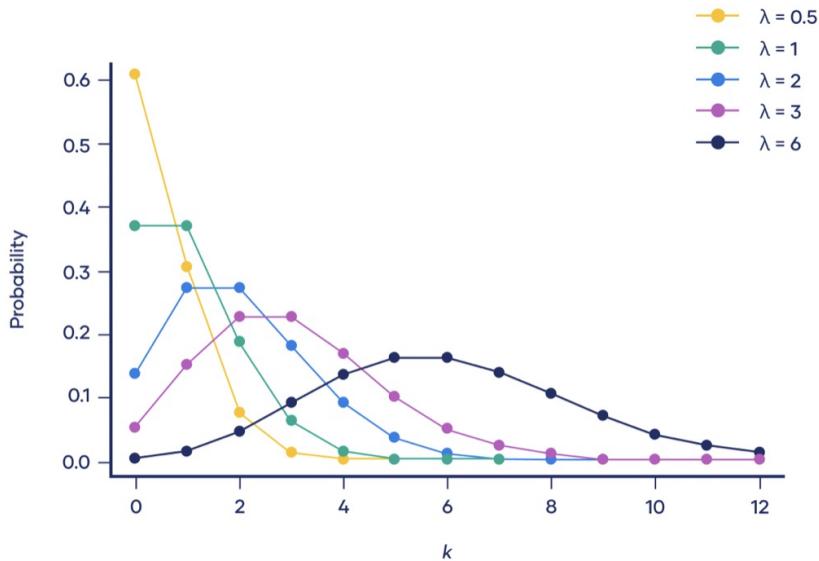
X_i, Y_i random variables (distributions)
↳ possible outcomes $0, 1, 2, 3, \dots$

$X \sim \text{Poisson}(\lambda)$ means

Outcomes $X \in \{0, 1, 2, 3, \dots\}$

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

$$\mathbb{E}X = \lambda, \text{var}(X) = \lambda, \lambda > 0$$



$$P\left(\sum_{i=1}^q X_i > R + \sum_{i=I+1}^q Y_i\right)$$

$$= \begin{cases} P\left(\sum_{i=1}^q \text{Poisson}(\lambda) > R + \sum_{i=I+1}^q \text{Poisson}(\lambda)\right) \\ \text{if } I < q \end{cases}$$

$$P\left(\sum_{i=1}^q \text{Poisson}(\lambda_i) > R\right) \quad \text{if } I=9$$

$$= \begin{cases} P\left[\text{Poisson}(q \cdot \lambda) > R + \text{Poisson}(q - (I+1))\lambda\right] \\ P\left(\text{Poisson}(q \cdot \lambda) > R\right) \quad \text{if } I=9 \end{cases}$$

Thm $\text{Poisson}(\lambda_1) + \text{Poisson}(\lambda_2) = \text{Poisson}(\lambda_1 + \lambda_2)$

$$= \begin{cases} P\left[\text{Skellam}(q\lambda_1, (q-I-1)\lambda_2) > R\right] \quad \text{if } I<9 \\ P\left[\text{Poisson}(q\lambda_1) > R\right] \quad \text{if } I=9 \end{cases}$$

Thm $\text{Poisson}(\lambda_1) \sim \text{Poisson}(\lambda_2)$
 $= \text{Skellam}(\lambda_1, \lambda_2)$

Now have an explicit formula for $f(I, R)$ if we assume

$$X_i, Y_i \sim \text{Poisson}(\lambda).$$

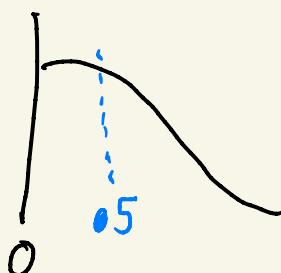
$\lambda = \mathbb{E} X_i$ = mean runs allowed in an inning by one team

Need to choose a smart value of λ

for a given league-season (e.g. 2019 NL)

let $\lambda = \text{observed mean runs allowed}$
in a half-inning

Code



$$X_i \sim \text{Poisson}(\lambda_x)$$

$$Y_i \sim \text{Poisson}(\lambda_y)$$

$$\lambda_x^{(m)}, \lambda_y^{(m)} \sim N_+(\lambda, \sigma^2)$$

$$f(R, I | \lambda_x, \lambda_y) =$$

$$P\left(\sum_{i=1}^q X_i > R + \sum_{i=I+1}^q Y_i\right)$$

$$+ \frac{1}{2} P\left(\sum_{i=1}^q X_i = R + \sum_{i=I+1}^q Y_i\right)$$

= a similar formula as before
except now in terms of λ_x, λ_y

$$f(I, R) = \frac{1}{M} \sum_{m=1}^M f(I, R | \lambda_x^{(m)}, \lambda_y^{(m)})$$

$$\left\{ \begin{array}{l} X_i \sim \text{Poisson}(\lambda_x) \\ Y_i \sim \text{Poisson}(\lambda_y) \\ \lambda_x^{(m)}, \lambda_y^{(m)} \sim N_+(\lambda, \sigma^2) \end{array} \right.$$

$$\lambda = \text{mean} \left(\left\{ \begin{array}{l} \text{mean} \\ \text{Runs scored in} \\ \text{half inning by} \\ \text{team } t \end{array} \right\} \right)$$

$$\sigma^2 = \text{var} \left(\left\{ \begin{array}{l} \text{g} \\ \text{g} \end{array} \right\} \right)$$

2019 NL: get $\hat{\lambda}, \hat{\sigma}^2$

then

$$f(I, R | \hat{\lambda}, \hat{\sigma}^2) = \frac{1}{M} \sum_{m=1}^M f(I, R | \lambda_x^{(m)}, \lambda_y^{(m)})$$

Where $\lambda_x^{(m)}, \lambda_y^{(m)} \sim N_+(\hat{\lambda}, \hat{\sigma}^2)$

$M = 100$

$$\begin{cases} X_i \sim \text{Poisson}(\lambda_x) \\ Y_i \sim \text{Poisson}(\lambda_y) \\ \lambda_x^{(m)}, \lambda_y^{(m)} \sim N_+(\lambda, \sigma^2 \cdot K) \end{cases}$$

$$K < 1$$

$$f(I, R | \hat{\lambda}, \sigma^2, K) = \frac{1}{M} \sum_{m=1}^M f(I, R | \lambda_x^{(m)}, \lambda_y^{(m)})$$

Where $\lambda_x^{(m)}, \lambda_y^{(m)} \sim N_+(\hat{\lambda}, \sigma^2 \cdot K)$

\hookrightarrow grid $f(I, R | \hat{\lambda}, \sigma^2, K)$

how to choose K ?

try different K 's and choose the K which works best, meaning matches the most accurate predictions.

WP prediction $f(I, R | \vec{\lambda}, \vec{\theta}^2, K)$
observed Win/loss column

log loss · (pred, obs. win/loss)