

TRUE
MILEAGE



Technology and Analytics for Usage-Based Auto Insurance (UBI)

Beyond GLMs

Nonparametric Regression

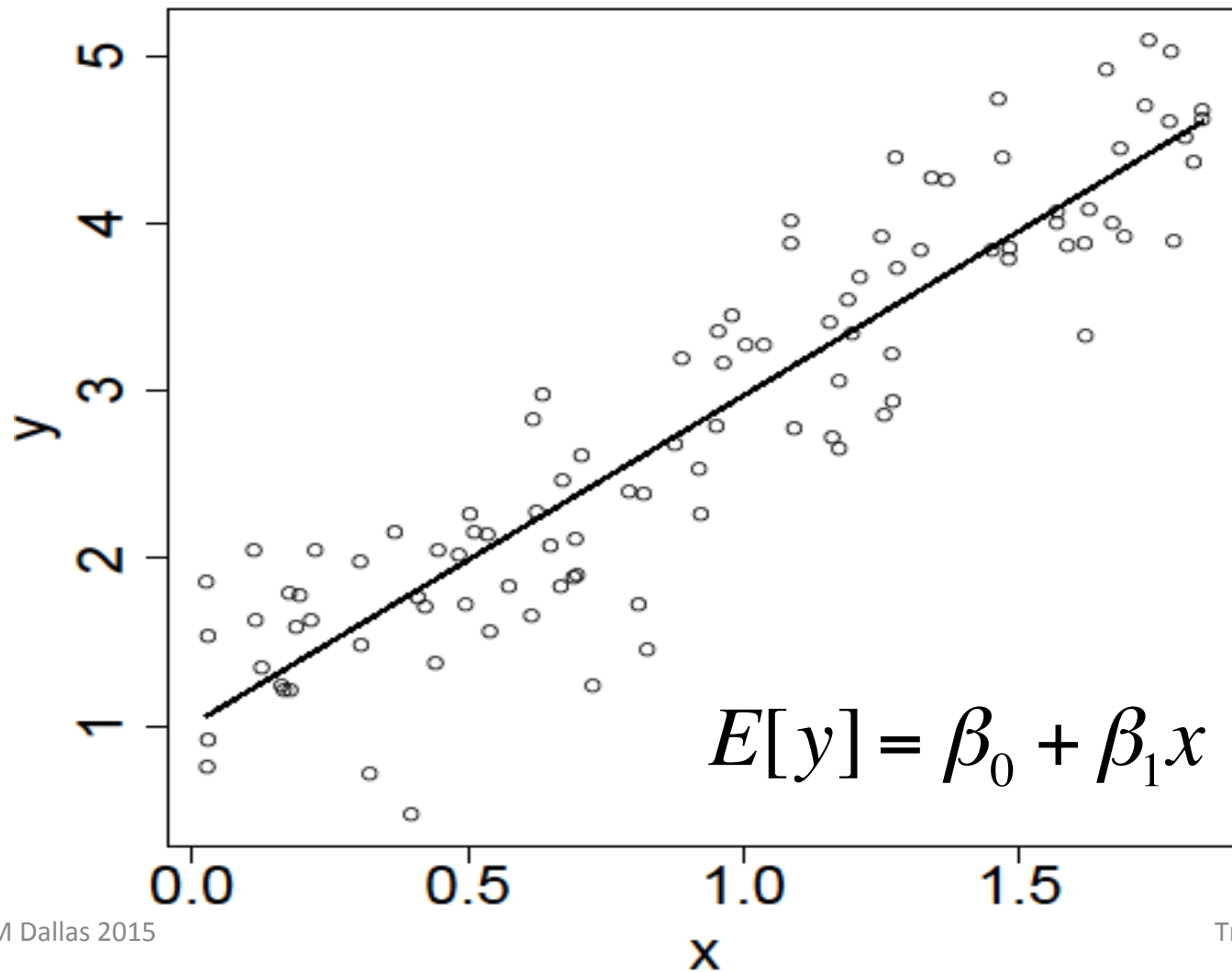


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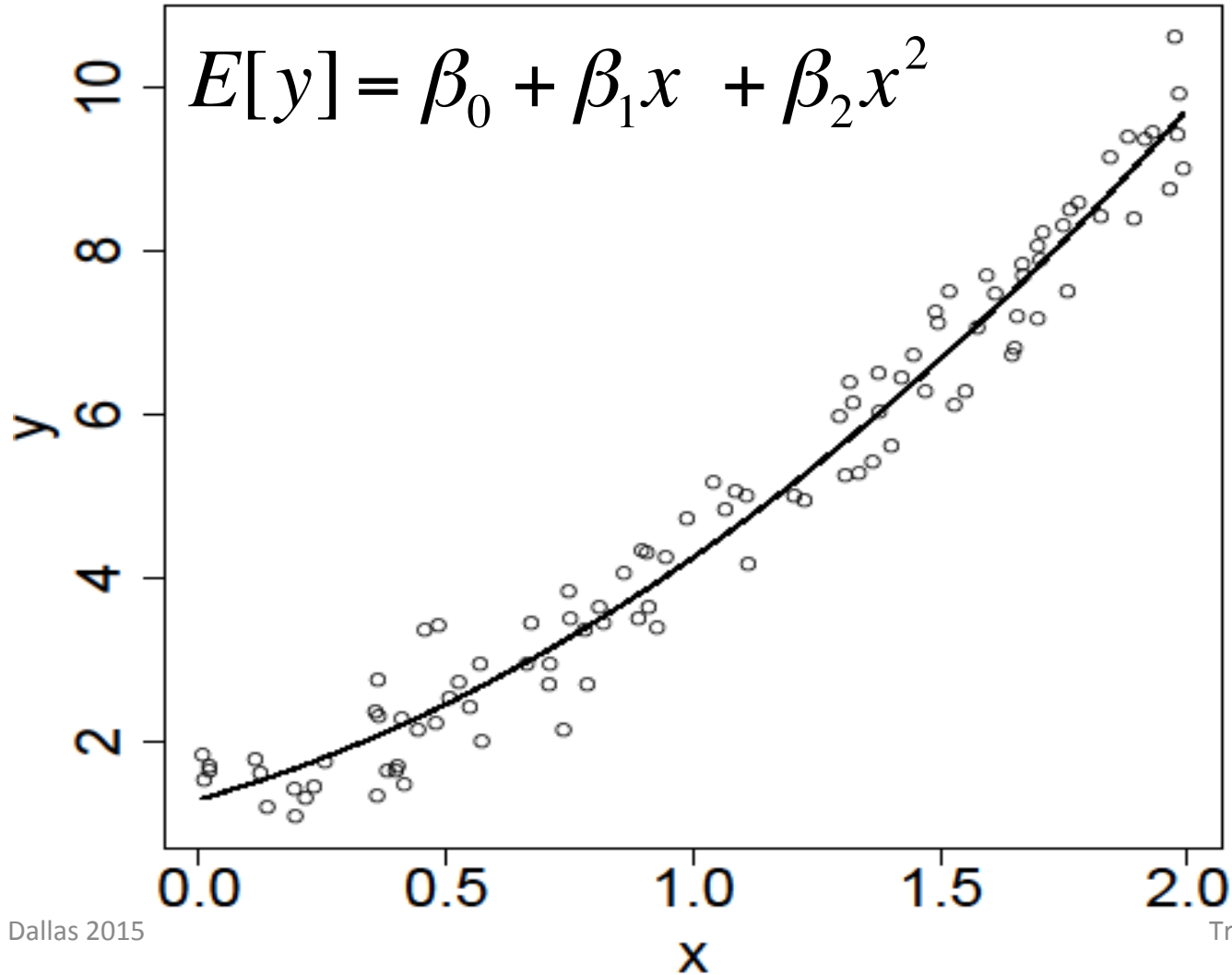
Ryan N. Morrison, CEO

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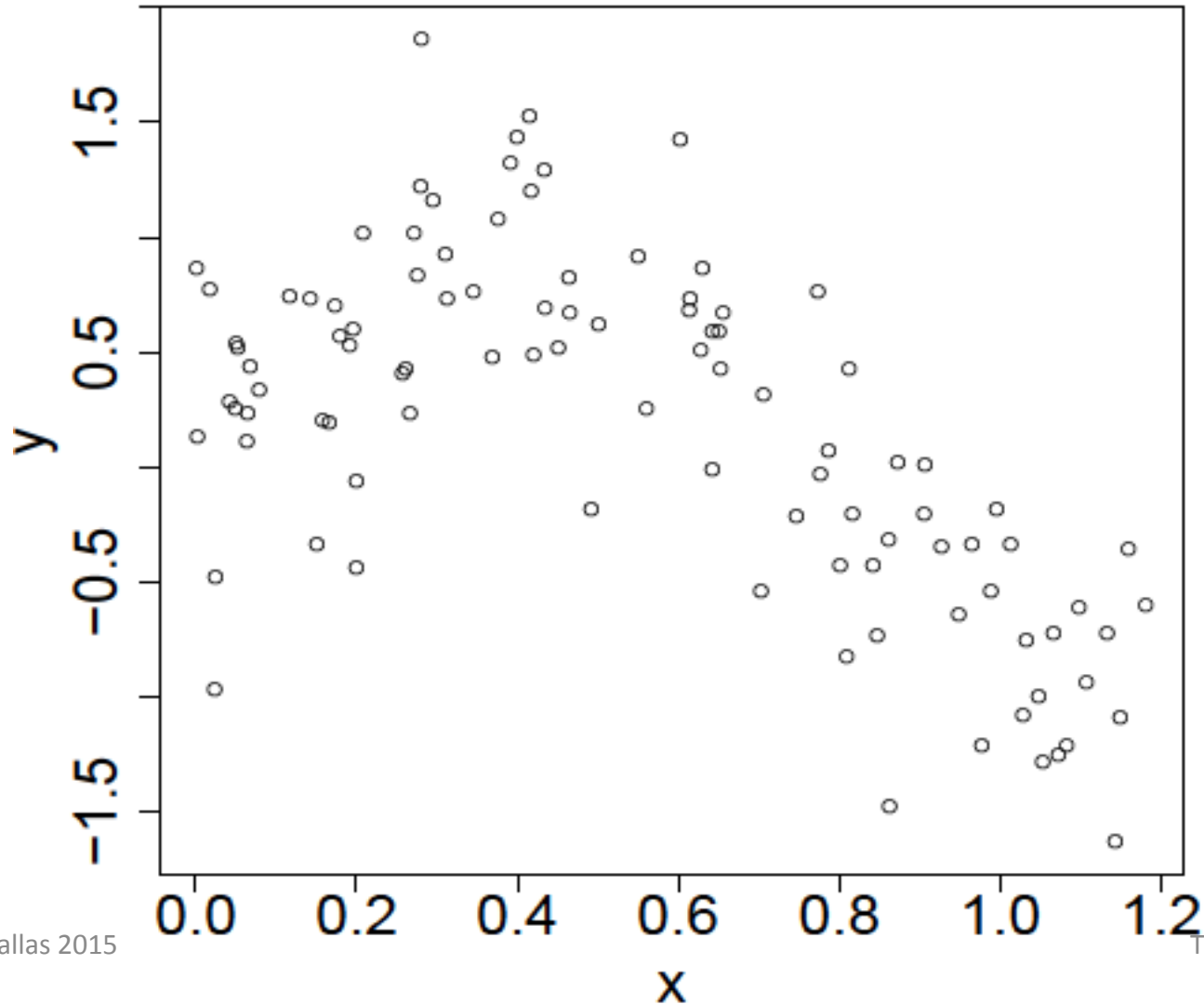
Linear Regression



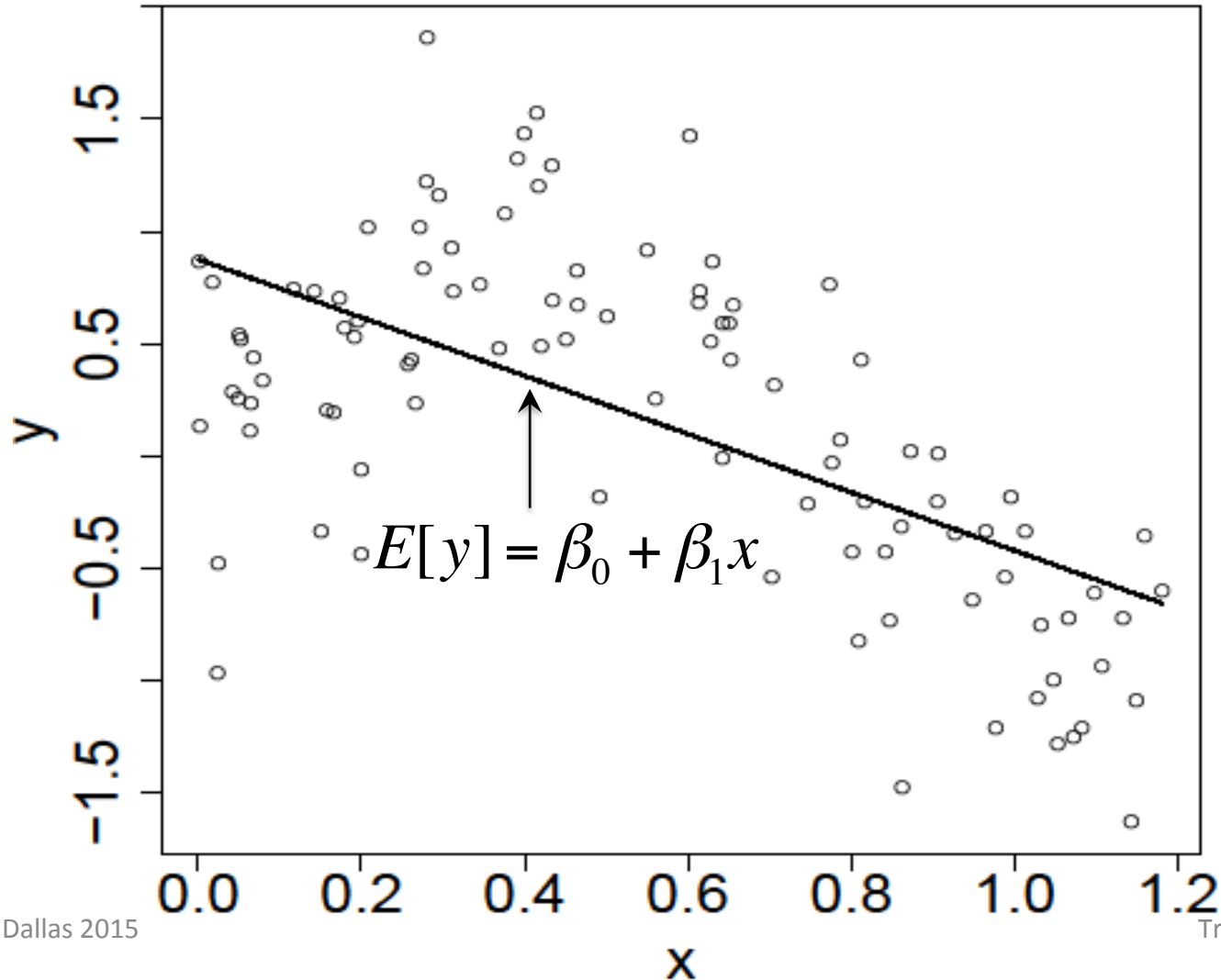
Polynomial Regression



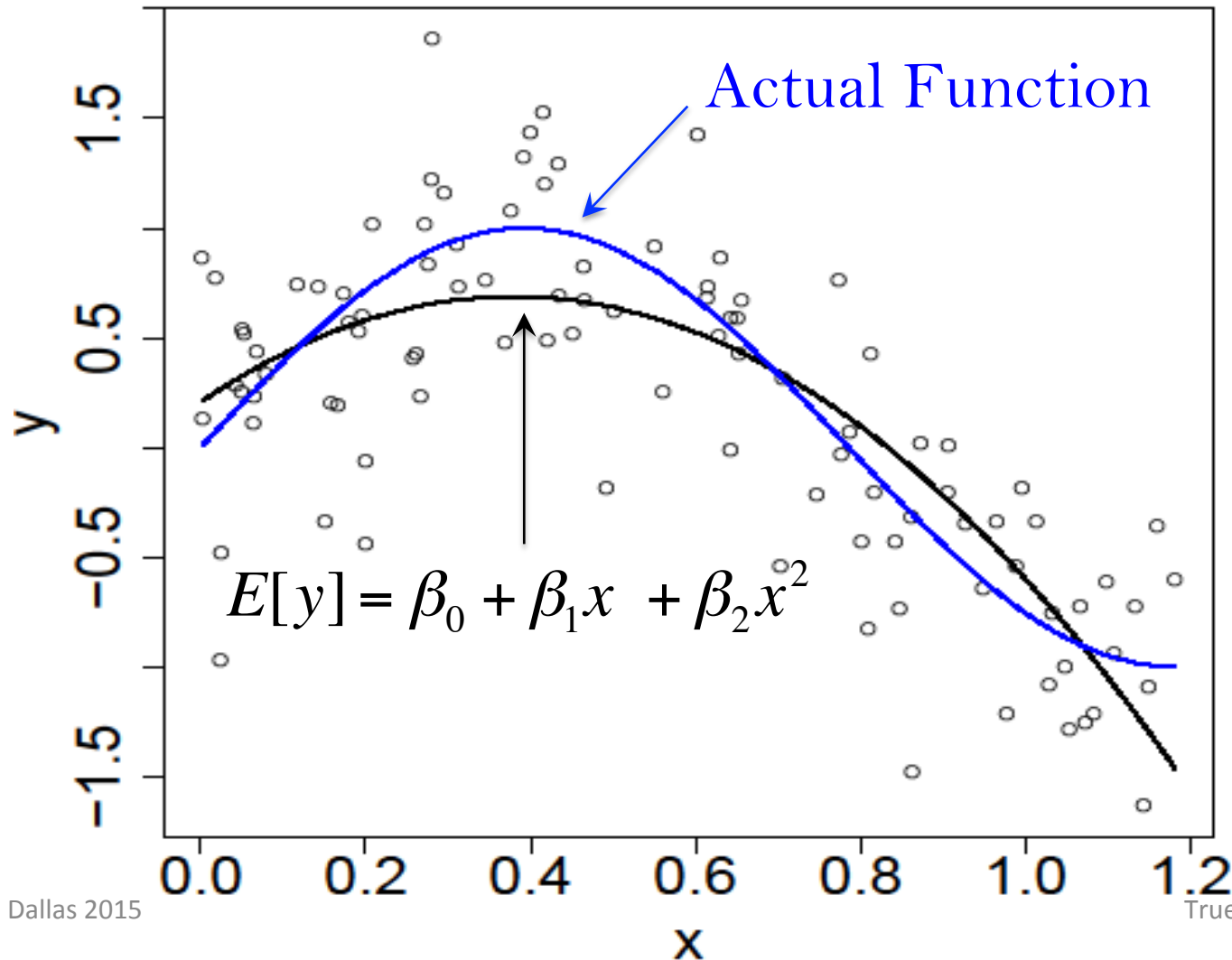
Data



Linear Regression



Polynomial Regression



Nonparametric Regression

Goal

- Given a scatterplot;
- We want to find a function $f(\mathbf{x})$ that best predicts the dependent variable y

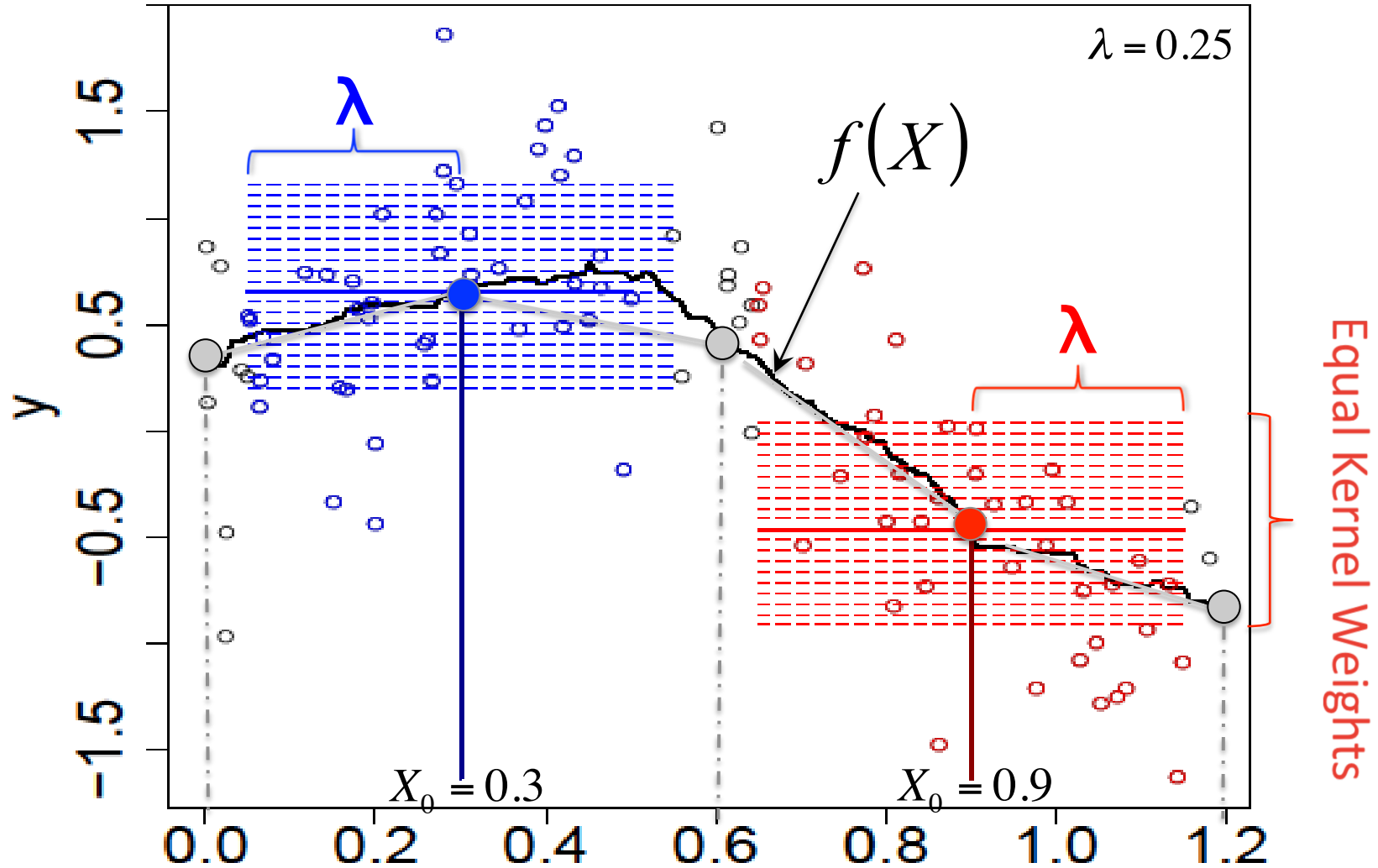


Nonparametric Regression

- Only use data in the neighborhood of X_0
- The neighborhood is set by bandwidth λ
- The regression weights are determined by a kernel function $K_\lambda(X_0, X_i)$
- Unique regression $f(X_0)$ at every X_0



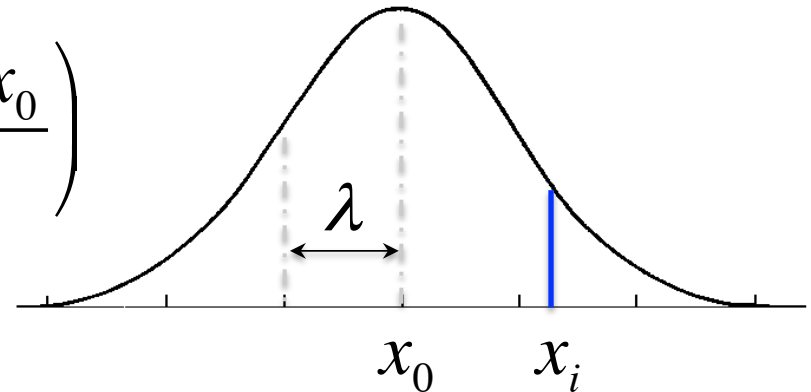
Local Average : Box Kernel



Nonparametric Regression

- The normal density is a popular kernel

$$K_{\lambda}(x_0, x_i) = \phi\left(\frac{x_i - x_0}{\lambda}\right)$$



- Nadaraya-Watson kernel-weighted estimate is

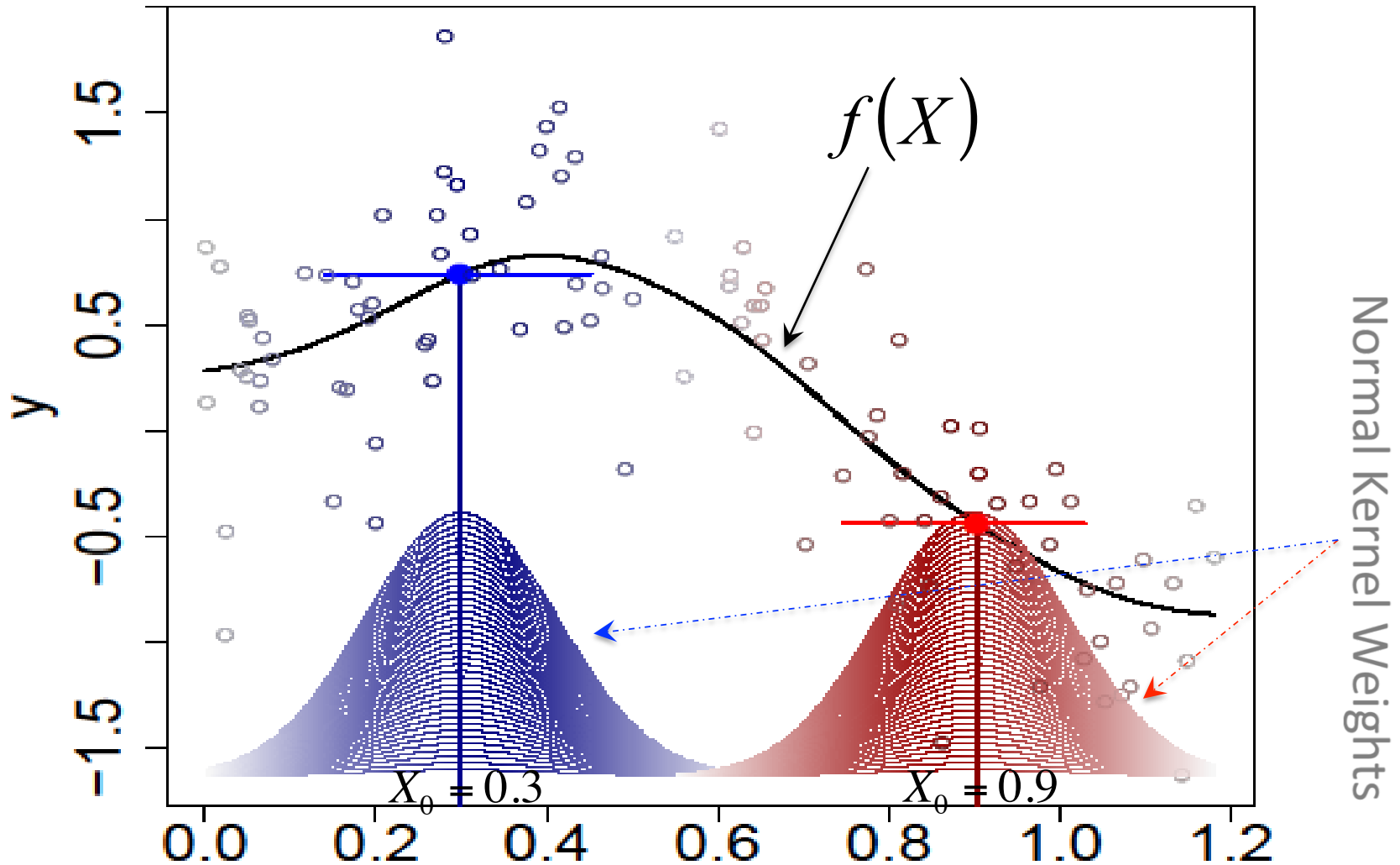
$$\hat{f}(x_0) = \sum_{i=1}^n \left(\frac{K_{\lambda}(x_0, x_i)}{\sum_{i=1}^n K_{\lambda}(x_0, x_i)} \right) y_i$$



Local Average : Normal Kernel

$$E[y] = \beta_0$$

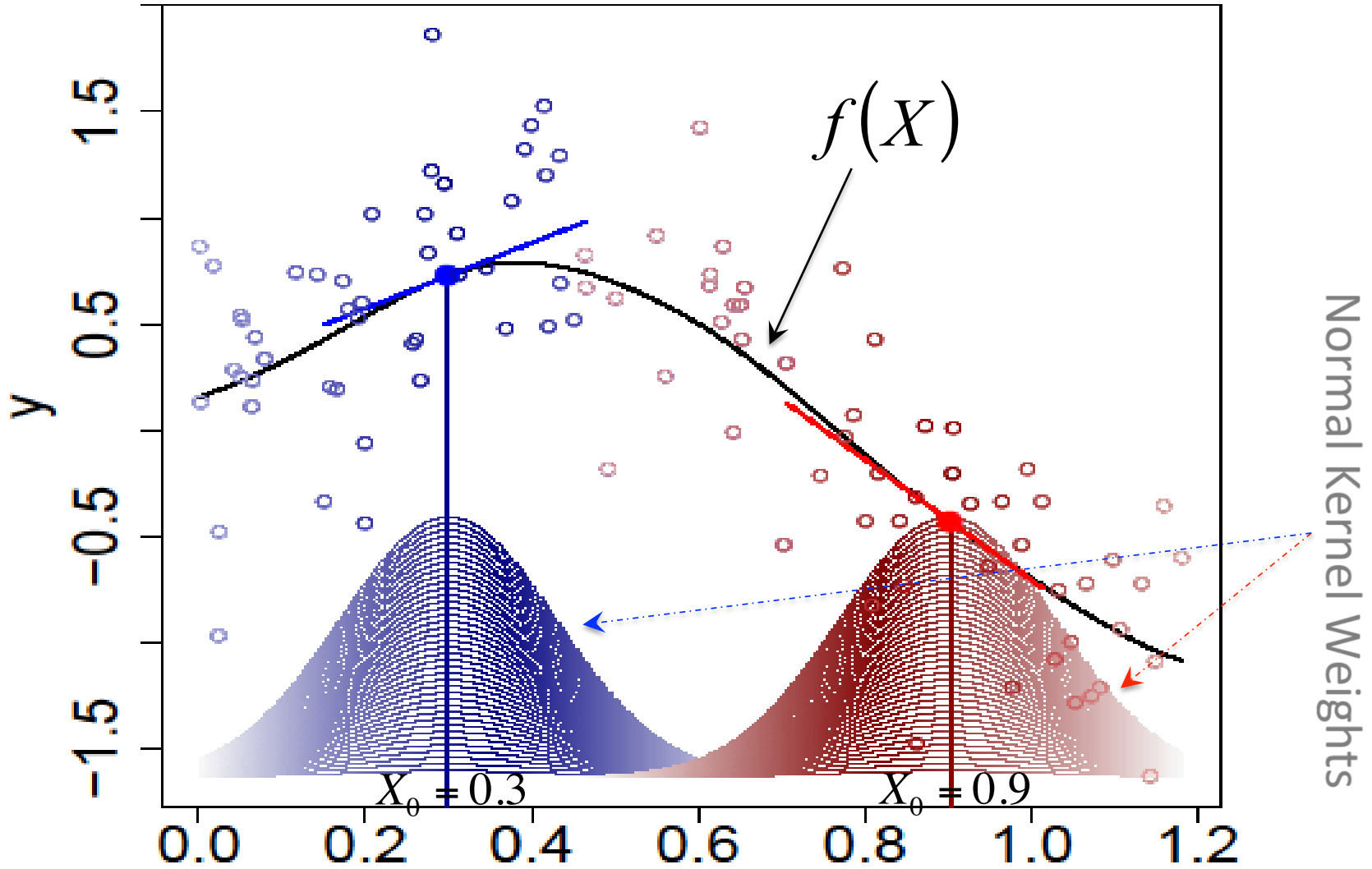
$$K_\lambda(x_0, x_i) = \phi\left(\frac{x_i - x_0}{\lambda}\right)$$



Local Linear : Normal Kernel

$$E[y] = \beta_0 + \beta_1 x$$

$$K_\lambda(x_0, x_i) = \phi\left(\frac{x_i - x_0}{\lambda}\right)$$



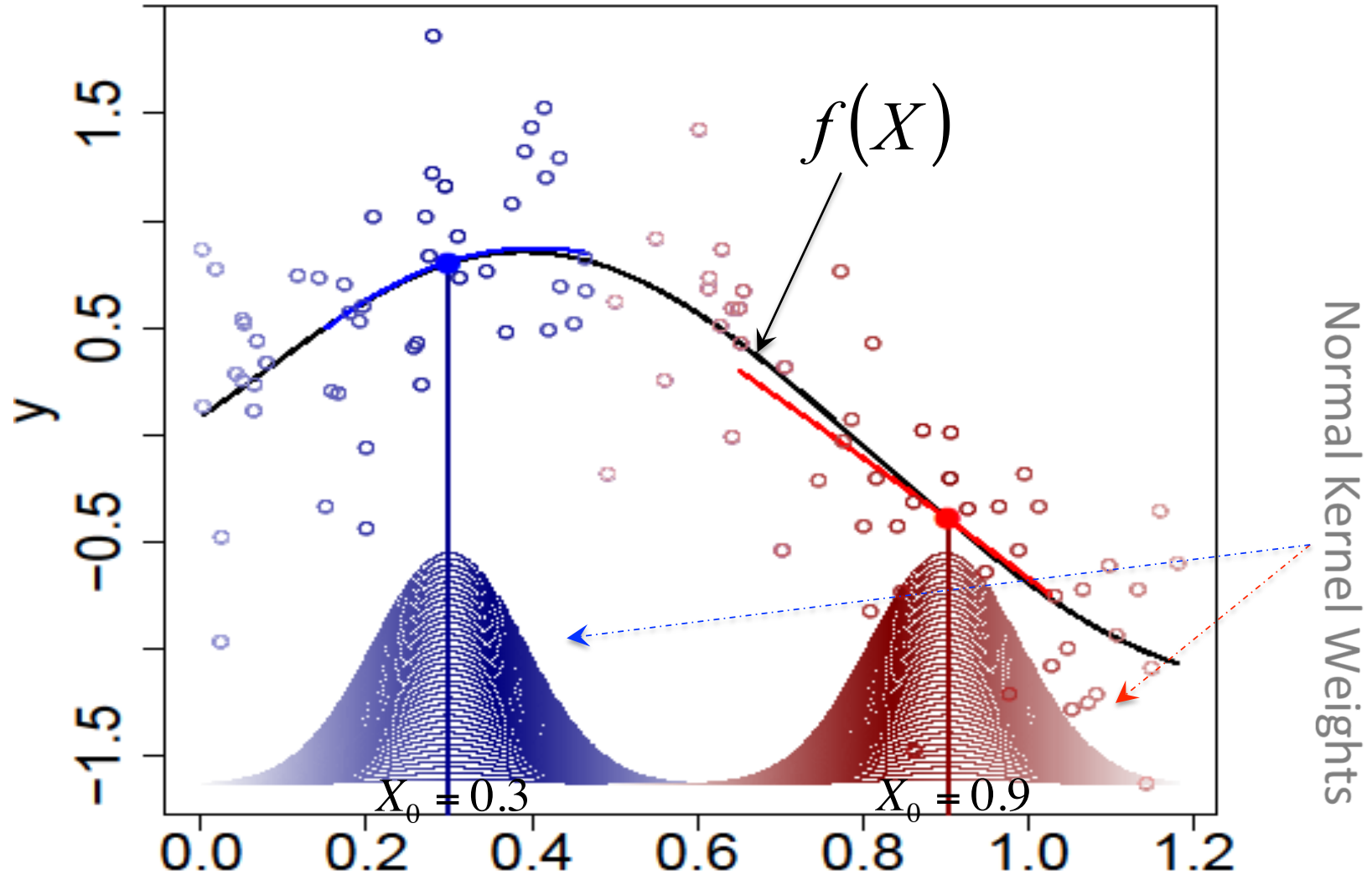
Normal Kernel Weights



Local Quadratic : Normal Kernel

$$E[y] = \beta_0 + \beta_1 x + \beta_2 x^2$$

$$K_\lambda(x_0, x_i) = \phi\left(\frac{x_i - x_0}{\lambda}\right)$$



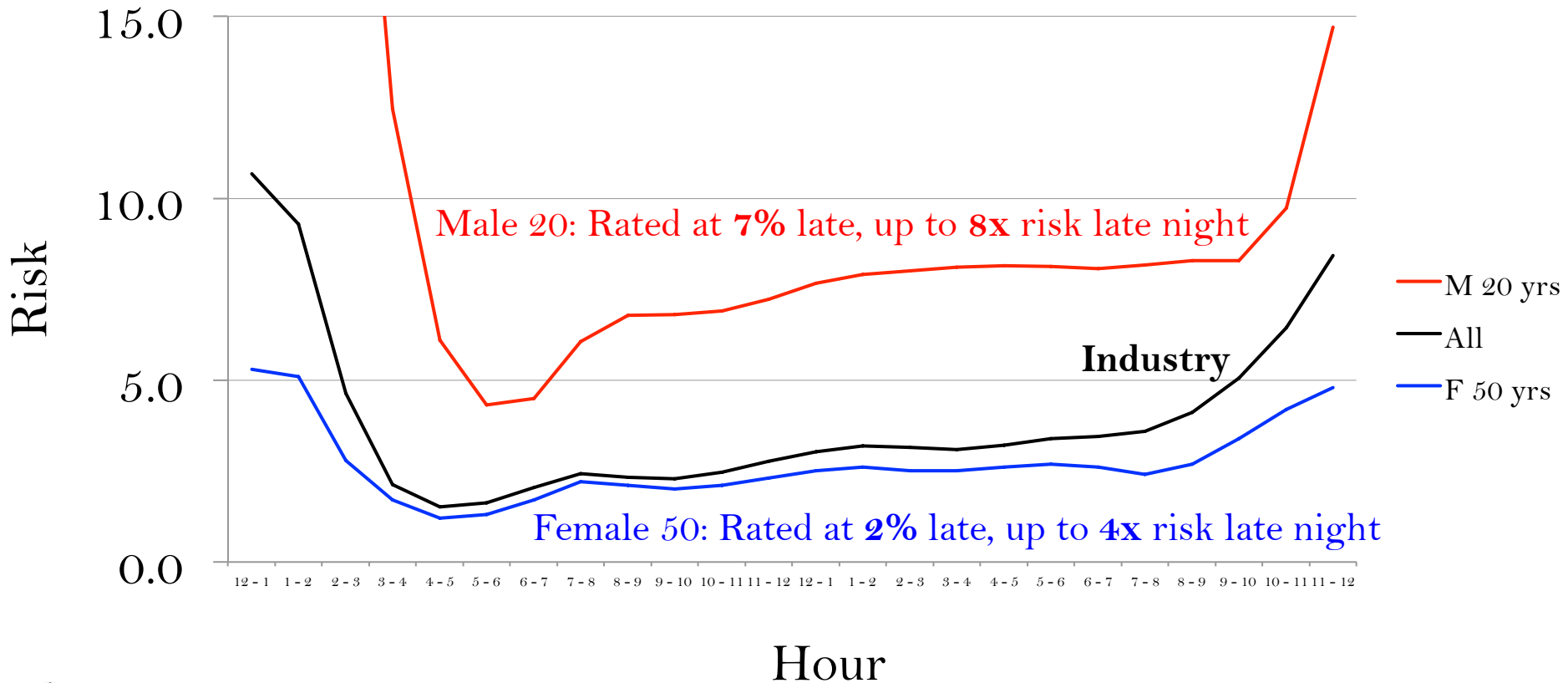
Nonparametric Regression

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Daytime Discount Analytics™

Risk by Time of Day



Mileage Discounts

Typical on-going verified mileage discounts today:

Mileage Up To	Discount
2,500	54%
5,000	39%
7,500	34%
10,000	26%
12,500	18%
15,000	13%
15,000 +	7%



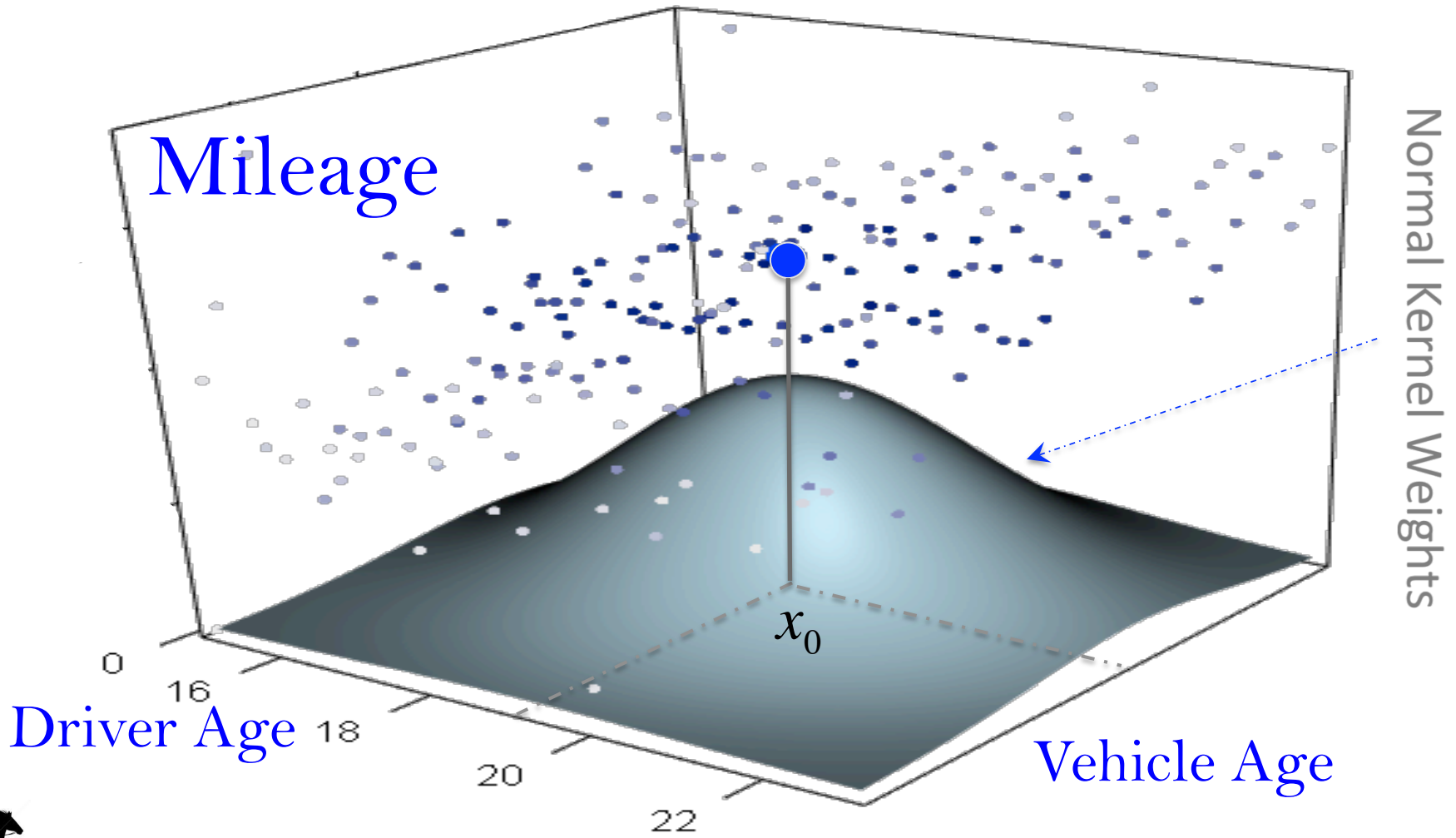
Mileage Discount Analytics™

Rating variables with the strongest mileage relationship?

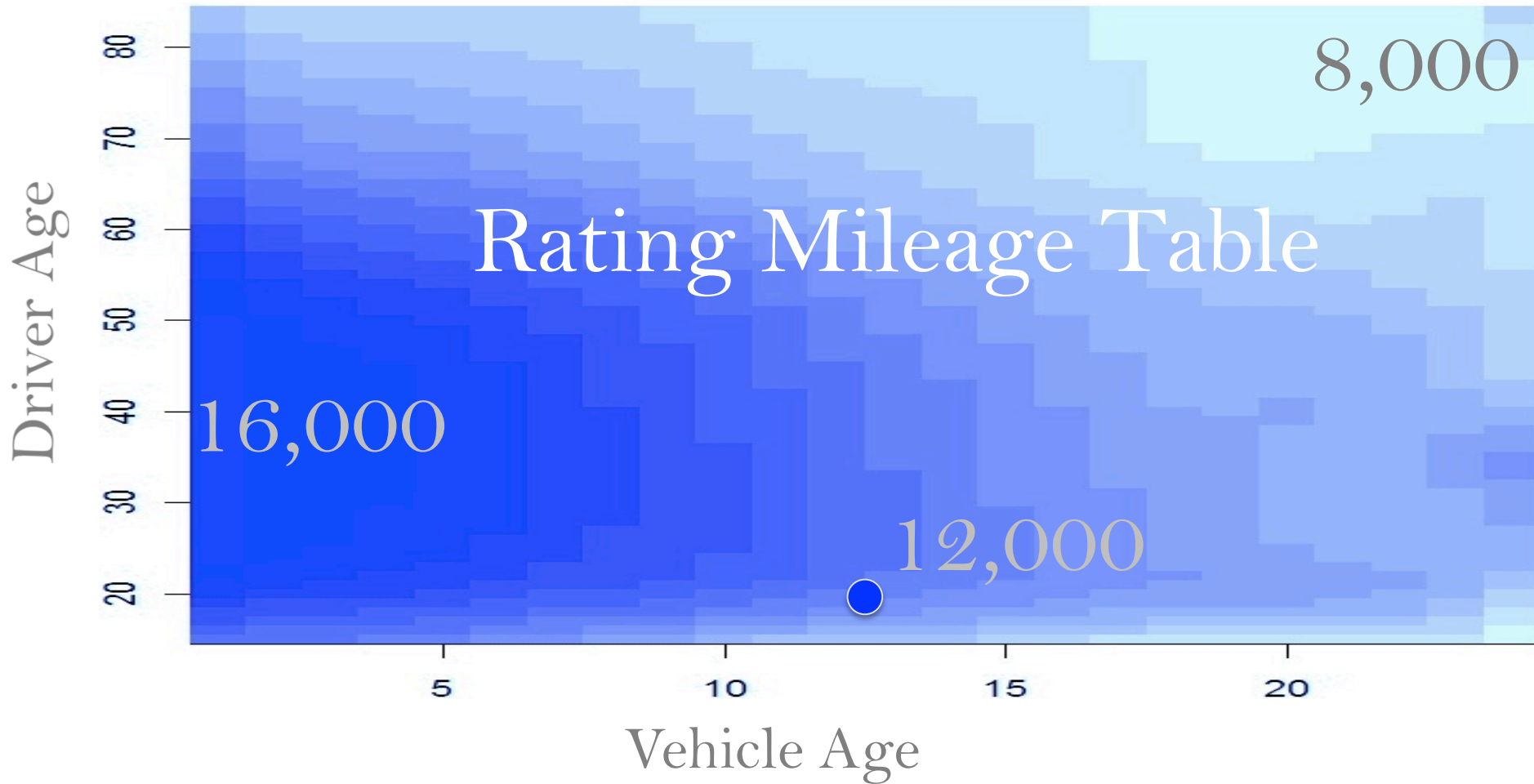
- Driver Age
- Driver Gender
- Urban vs. Rural
- Drivers/Vehicles
- Vehicle Type
- Vehicle Age



Mileage Discount Analytics™



Mileage Discount Analytics™



Mileage Discount Analytics™

$$\text{Max Discount} \cdot \left(1 - \frac{\text{Mileage}}{\text{Rating Mileage}} \right)$$

Example 1:

(new car and mid-age driver)

$$50\% \cdot \left(1 - \frac{10,000}{\mathbf{16,000}} \right) = \mathbf{19\%}$$

Example 2:

(older car)

$$50\% \cdot \left(1 - \frac{10,000}{\mathbf{10,000}} \right) = \mathbf{0\%}$$



TRUE
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Thank You!

Visit True Mileage at Booth #8



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