PSY9511: Seminar 5

Beyond linearity: Extensions of linear models and tree-based models

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24.09.24

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Outline

1. Exercise 3
2. Exercise 4
3. Recap
4. Extensions of linear models
   4.1 Generalized linear models (GLMs)
   4.2 Generalized additive models (GAMs)
5. Tree-based models
   5.1 Decision trees
   5.2 Random forests
   5.3 Gradient boosting (XGBoost)
6. Neural networks (Lecture 7/8)

Exercise 3

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Exercise 3: Backward stepwise selection

http://localhost:8888/notebooks/notebooks%2FBackward%20selection.ipynb

Exercise 3: Lasso

http://localhost:8888/notebooks/notebooks/Lasso.ipynb

Exercise 4

Extensions of linear models

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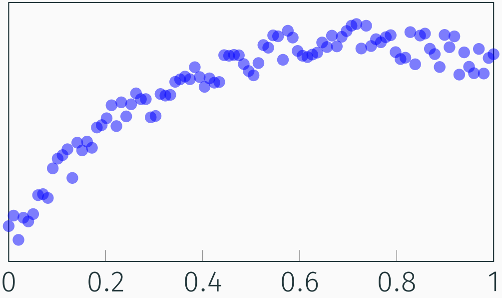
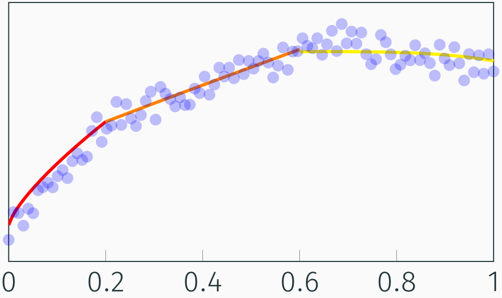
Extensions of linear models: Generalized additive models



Splines: Piecewise polynomial functions

Extensions of linear models: Generalized additive models



Splines: Piecewise polynomial functions

- Regression splines (ISL, Chapter 7.4)
- Smoothing splines (This lecture)

Extensions of linear models: Generalized additive models

$$\sum_{i=1}^{n}(y_i - g(x_i))^2 + \lambda \int g''(t)^2 dt$$

Extensions of linear models: Generalized additive models

$$\hat{y}_i = g(x_i)$$

$$\sum_{i=1}^{n}(y_i - g(x_i))^2 + \lambda \int g''(t)^2 dt$$

Extensions of linear models: Generalized additive models

$$\sum_{i=1}^{n}(y_i - g(x_i))^2 + \lambda \int g''(t)^2 dt$$

$$\uparrow$$

$$\sum(y_i - \hat{y}_i)^2$$

Extensions of linear models: Generalized additive models

$$\sum_{i=1}^{n}(y_i - g(x_i))^2 + \lambda \int g''(t)^2 dt$$

Large when g is wiggly

Extensions of linear models: Generalized additive models

Balances what is
most important

$$\sum_{i=1}^{n}(y_i - g(x_i))^2 + \underbrace{\lambda}_{\text{}} \int g''(t)^2 dt$$

Tries to
fit data

Tries to
simplify g

Extensions of linear models: Generalized additive models

http://localhost:8888/notebooks/notebooks/Smoothing%20spline.ipynb

Extensions of linear models: Generalized additive models

$$\hat{y} = \beta_0 + \beta_1 x \qquad\qquad \hat{y} = g(x)$$

Extensions of linear models: Generalized additive models

$$\hat{y} = \beta_0 + \beta_1 x \quad \longrightarrow \quad \hat{y} = \beta_0 + \sum_{j=1}^{p} \beta_j x_j$$

$$\hat{y} = g(x) \quad \longrightarrow \quad \hat{y} = \beta_0 + \sum_{j=1}^{p} f_j(x_j)$$

Extensions of linear models: Generalized additive models

Generalized additive models (GAMs):
Extends upon the regular linear model by allowing for non-linear functions f_j to be fitted for each predictor x_j.

- Does not allow for interactions between predictors.

Tree-based models

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