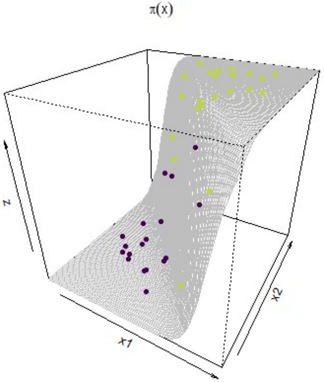
Interpretable Machine Learning

Generalized Linear Models

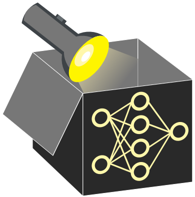


Learning goals

- Definition of GLMs
- Logistic regression as example
- Interpretation in logistic regression

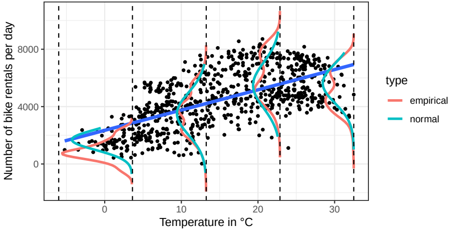
GENERALIZED LINEAR MODEL (GLM)

▸ Nelder and Wedderburn 1972



Problem: Target variable given feat. not always normally dist. $\rightsquigarrow$ LM not suitable

- Target is binary (e.g., disease classification)
  $\rightsquigarrow$ Bernoulli / Binomial distribution
- Target is count variable
  (e.g., number of sold products)
  $\rightsquigarrow$ Poisson distribution
- Time until an event occurs
  (e.g., time until death)
  $\rightsquigarrow$ Gamma distribution



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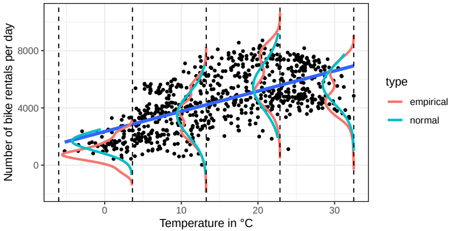


Solution: GLMs - extend LMs by allowing other distributions from exponential family

$$g(\mathbb{E}(y \mid \mathbf{x})) = \mathbf{x}^\top \boldsymbol{\theta} \;\Leftrightarrow\; \mathbb{E}(y \mid \mathbf{x}) = g^{-1}(\mathbf{x}^\top \boldsymbol{\theta})$$

- Link function g links linear predictor $\mathbf{x}^\top \boldsymbol{\theta}$ to expectation of distribution of $y \mid \mathbf{x}$
  ⇝ LM is special case: Gaussian distribution for $y \mid \mathbf{x}$ with g as identity function
- Link function g and distribution need to be specified
- High-order and interaction effects can be manually added as in LMs
- Note: Interpretation of weights depend on link function and distribution

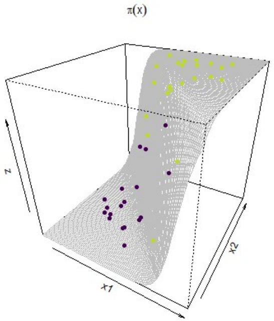
GLM - LOGISTIC REGRESSION

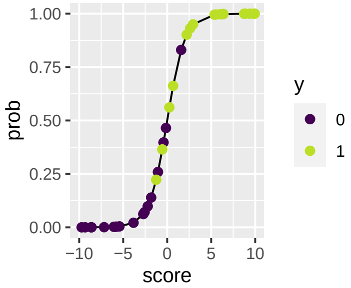
- Logistic regression $\hat{=}$ GLM with Bernoulli distribution and logit link function:

$$g(x) = \log\left(\frac{x}{1-x}\right) \Rightarrow g^{-1}(x) = \frac{1}{1+\exp(-x)}$$

- Models probabilities for binary classification by

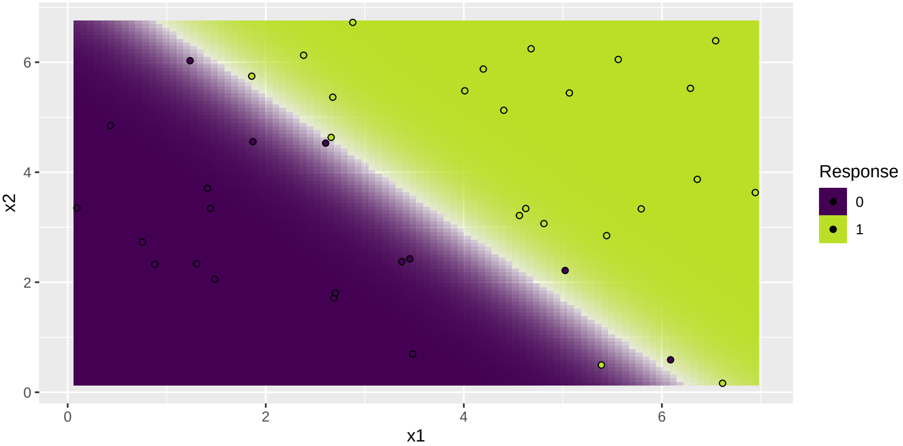
$$\pi(\mathbf{x}) = \mathbb{E}(y \mid \mathbf{x}) = P(y = 1) = g^{-1}(\mathbf{x}^\top \boldsymbol{\theta}) = \frac{1}{1+\exp(-\mathbf{x}^\top \boldsymbol{\theta})}$$



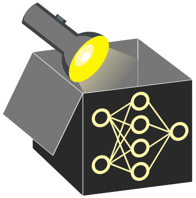


GLM - LOGISTIC REGRESSION

- Typically, we set the threshold to 0.5 to predict classes, e.g.,
  - Class 1 if $\pi(\mathbf{x}) > 0.5$
  - Class 0 if $\pi(\mathbf{x}) \leq 0.5$



GLM - LOGISTIC REGRESSION - INTERPRETATION

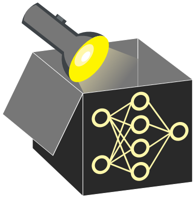


- **Recall:** Odds is ratio of two probabilities, odds ratio compares ratio of two odds
- Weights θ_j are interpreted linear as in LM (but w.r.t. log-odds)
  $\rightsquigarrow$ difficult to comprehend

$$\textit{log-odds} = \log\left(\frac{\pi(\mathbf{x})}{1-\pi(\mathbf{x})}\right) = \log\left(\frac{P(y=1)}{P(y=0)}\right) = \theta_0 + \theta_1 x_1 + \ldots + \theta_p x_p$$

Interpretation:
Changing x_j by one unit, changes log-odds of class 1 compared to class 0 by θ_j

GLM - LOGISTIC REGRESSION - INTERPRETATION



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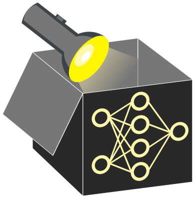
- Odds for class 1 vs. class 0: $\textit{odds} = \frac{\pi(\mathbf{x})}{1-\pi(\mathbf{x})} = \exp(\theta_0 + \theta_1 x_1 + \ldots + \theta_p x_p)$
- Instead of interpreting changes w.r.t. log-odds, *odds ratio* is more common

$$= \frac{\textit{odds}_{x_j+1}}{\textit{odds}} = \frac{\exp(\theta_0 + \theta_1 x_1 + \ldots + \theta_j(x_j+1) + \ldots + \theta_p x_p)}{\exp(\theta_0 + \theta_1 x_1 + \ldots + \theta_j x_j + \ldots + \theta_p x_p)} = \exp\left(\theta_j\right)$$

Interpretation: Changing x_j by one unit, changes the **odds ratio** for class 1 (compared to class 0) by the **factor** $\exp(\theta_j)$

GLM - LOGISTIC REGRESSION - EXAMPLE



- Create a binary target variable for bike rental data:
  - Class 1: “high number of bike rentals” $>$ 70% quantile (i.e., $\texttt{cnt} > 5531$)
  - Class 0: “low to medium number of bike rentals” (i.e., $\texttt{cnt} \leq 5531$)
- Fit a logistic regression model (GLM with Bernoulli distribution and logit link)

	Weights	SE	p-value
(Intercept)	-8.52	1.21	0.00
seasonSPRING	1.74	0.60	0.00
seasonSUMMER	-0.86	0.77	0.26
seasonFALL	-0.64	0.55	0.25
temp	0.29	0.04	0.00
hum	-0.06	0.01	0.00
windspeed	-0.09	0.03	0.00
days_since_2011	0.02	0.00	0.00

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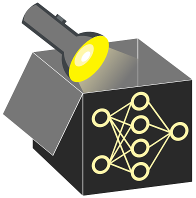

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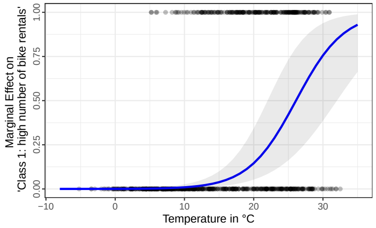

Interpretation

- If `temp` increases by $1^\circ C$, odds ratio for class 1 increases by factor $\exp(0.29) = 1.34$ compared to class 0, c.p. ($\hat{=}$ “high number of bike rentals” now 1.34 times more likely)