

CS 66: Machine Learning

Prof. Sara Mathieson

Spring 2019



- **Lab 3 due Thursday** (you should be close to done by lab on Wed)
- Midterm 1 Feb 27 (in lab)
 - Let me know ASAP about accommodations
- Office Hours **TODAY 12:30-2pm**
- Choose partner for Lab 4 by Tues night

Research Talk

Monday, February 18, 2019

11:30-12:30 p.m.

Science Center 240

Michael Wehar

Temple University

“Formal Language Theory and Applications”

Outline for February 18

- Intuition behind logistic regression
- Gradient descent for logistic regression
- Multi-class logistic regression

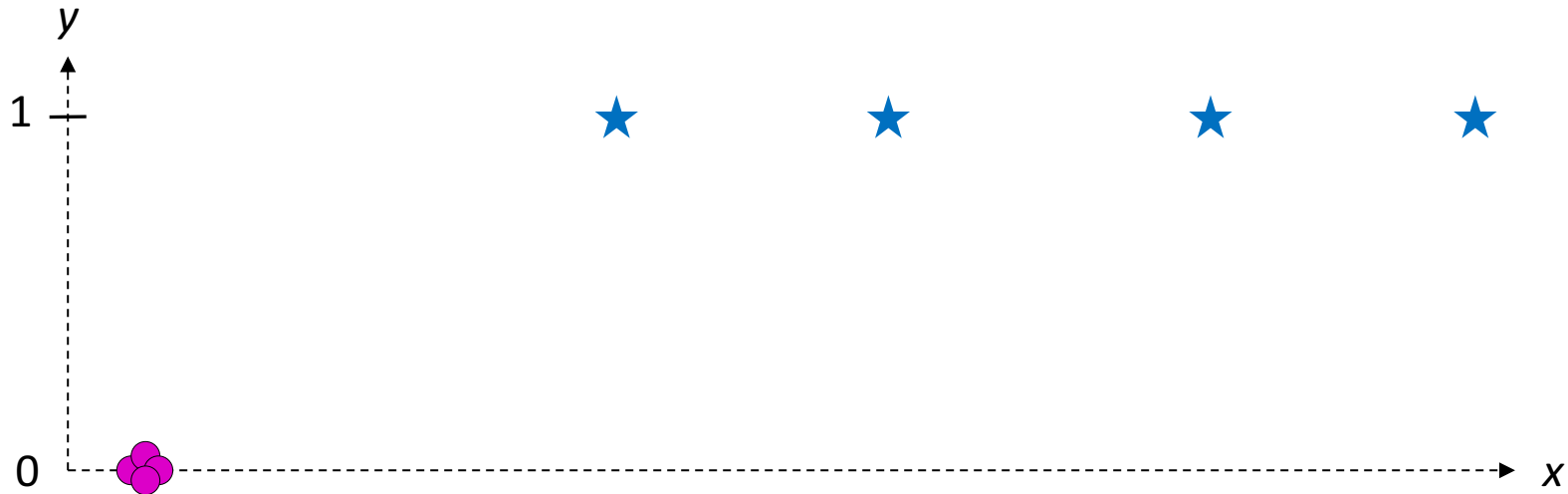
Soon: statistical evaluation

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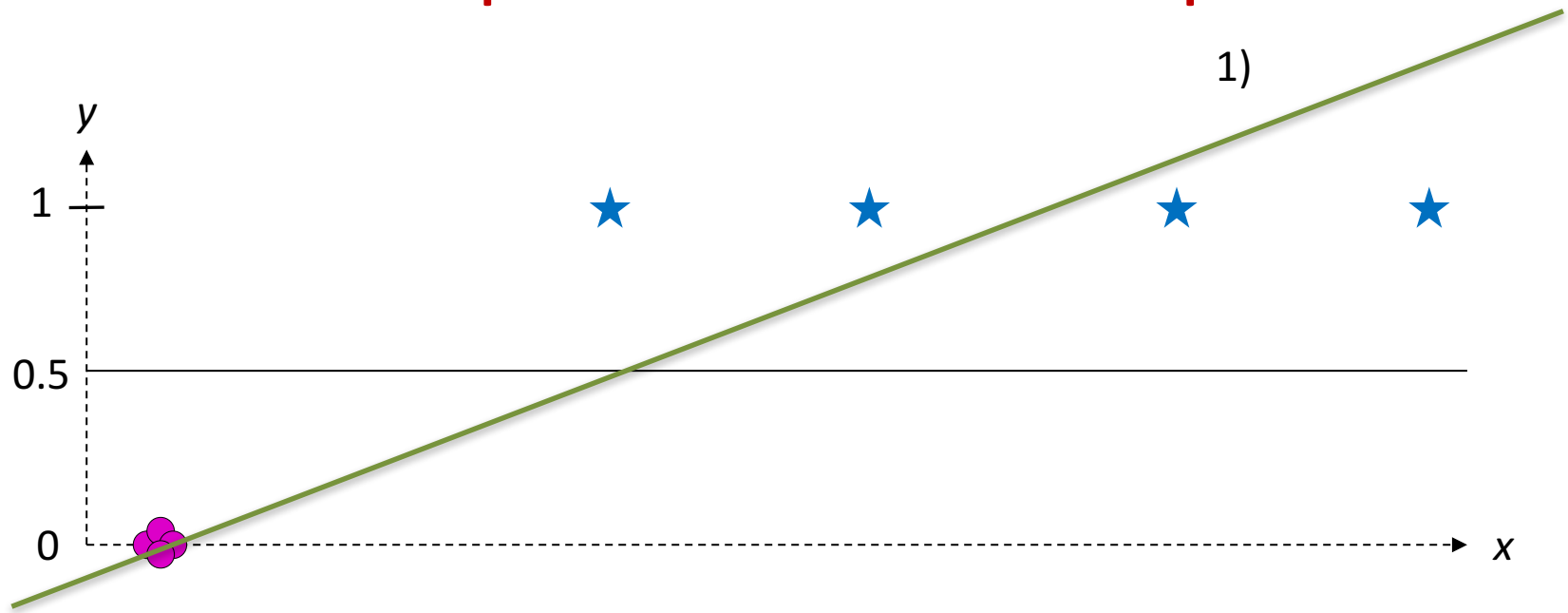
Soon: statistical evaluation

Informal quiz: discuss with a partner



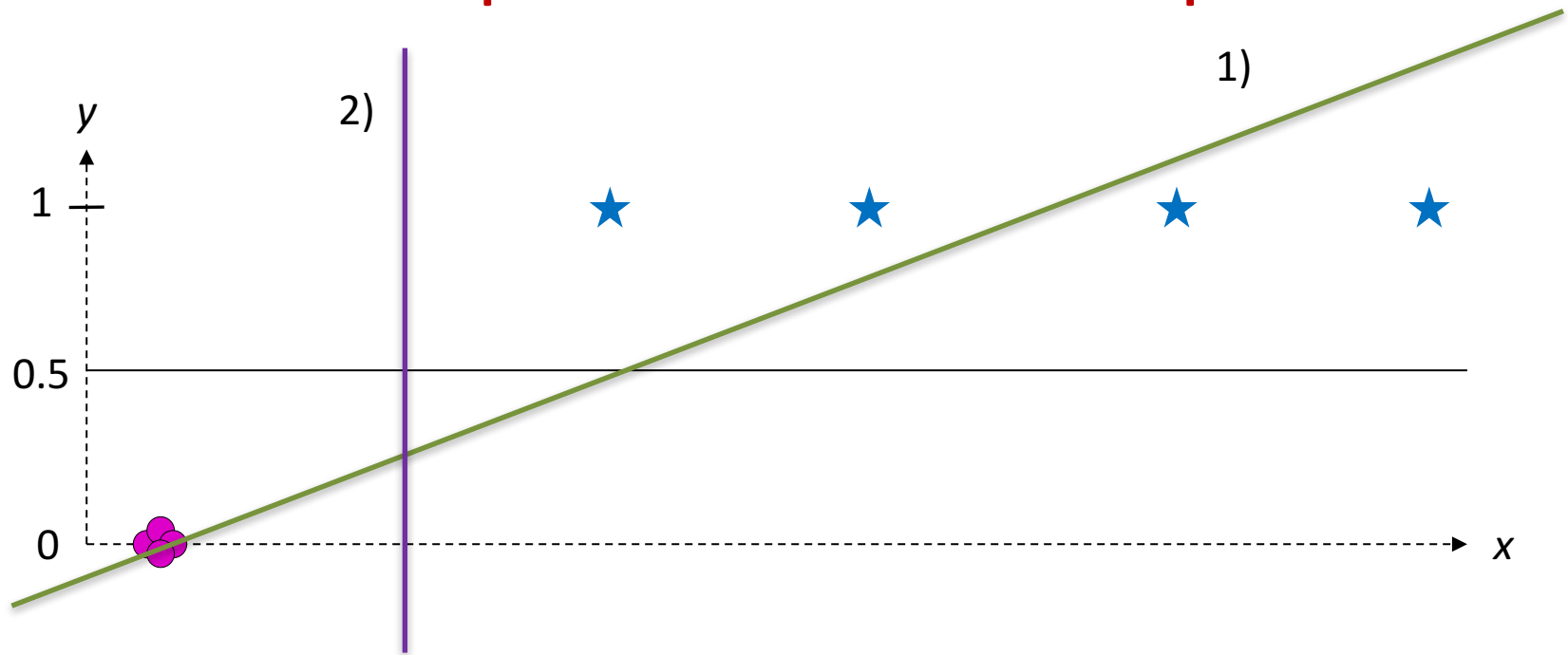
- 1) What line of best fit would be produced by linear regression? (roughly)
- 2) What linear decision boundary would be produced by logistic regression? (roughly)

Informal quiz: discuss with a partner



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Logistic Regression

Likelihood function

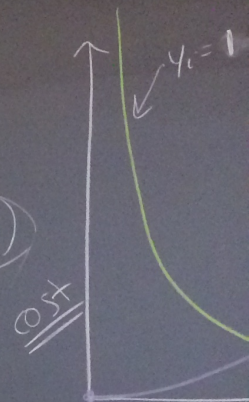
minimize $\left\{ \begin{array}{l} \boxed{\text{cost}} \\ \rightarrow \text{negative} \\ \text{log} \\ \text{likelihood} \end{array} \right.$

$$L(\vec{b}) = \prod_{i=1}^n \underbrace{(h_{\vec{b}}(\vec{x}_i))^{y_i}}_{\text{prob } y_i=1} \underbrace{(1-h_{\vec{b}}(\vec{x}_i))^{1-y_i}}_{\text{prob } y_i=0}$$

$$J(\vec{b}) = - \sum_{i=1}^n y_i \log h_{\vec{b}}(\vec{x}_i) - \sum_{i=1}^n (1-y_i) \log (1-h_{\vec{b}}(\vec{x}_i))$$

$$\boxed{\text{cost}} = \begin{cases} -\log h_{\vec{b}}(\vec{x}_i) & \text{if } y_i=1 \\ -\log (1-h_{\vec{b}}(\vec{x}_i)) & \text{if } y_i=0 \end{cases}$$

(for \vec{x}_i)

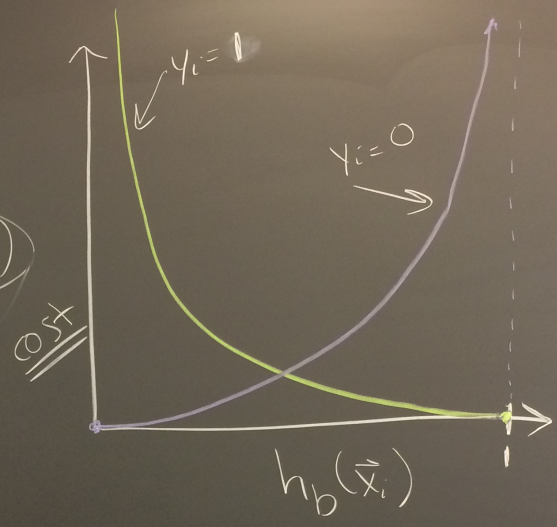


y_i

$$\sum_i \frac{(1-y_i) \log(1-h_b(\bar{x}_i))}{1}$$

$y_i = 1$

$f \quad y_i = 0$



$$\frac{\partial J}{\partial b_i}$$

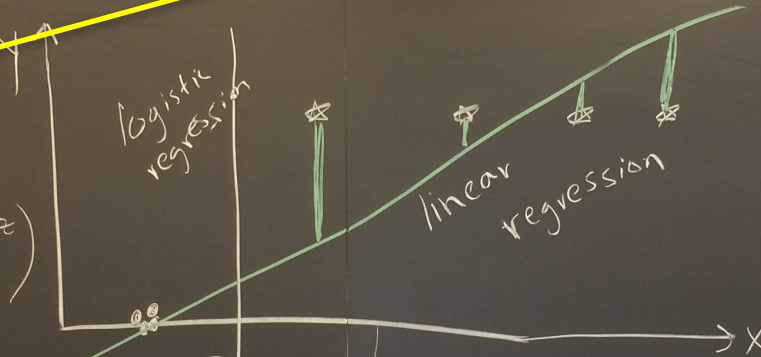
"Inside function" does not include the negative, we already dealt with that!

$$g(z) = \frac{1}{1 + e^{-z}} = (1 + e^{-z})^{-1}$$

$$g'(z) = -1(1 + e^{-z})^{-2}(-e^{-z})$$

EXERCISE

$$g'(z) = g(z)(1 - g(z))$$



$$h_b^T(\vec{x}) = \frac{1}{1 + e^{-\vec{b}^T \vec{x}}}$$

inside function

$$\begin{aligned} \hat{b}_0 + \hat{b}_1 x &= 0 \\ \Rightarrow x &= -\frac{\hat{b}_0}{\hat{b}_1} \end{aligned}$$

$$\left. \begin{aligned} h_b^T(\vec{x}) &\geq 0.5 \Rightarrow \hat{y} = 1 \\ h_b^T(\vec{x}) &< 0.5 \Rightarrow \hat{y} = 0 \end{aligned} \right\} \begin{aligned} \vec{b}^T \vec{x} &\geq 0 \\ \vec{b}^T \vec{x} &< 0 \end{aligned}$$

$$\frac{\partial J}{\partial b_j} = \left[-\frac{y_i}{h_b(\bar{x}_i)} + \frac{(1-y_i)}{1-h_b(\bar{x}_i)} \right] \frac{\partial h_b(\bar{x}_i)}{\partial b_j}$$

$$= \left[-\frac{y_i}{h_b(\bar{x}_i)} + \frac{(1-y_i)}{1-h_b(\bar{x}_i)} \right] h_b(\bar{x}_i)(1-h_b(\bar{x}_i))(+x_{ij})$$

$$= \left[-y_i(1-h_b(\bar{x}_i)) + (1-y_i)(h_b(\bar{x}_i)) \right] (+x_{ij})$$

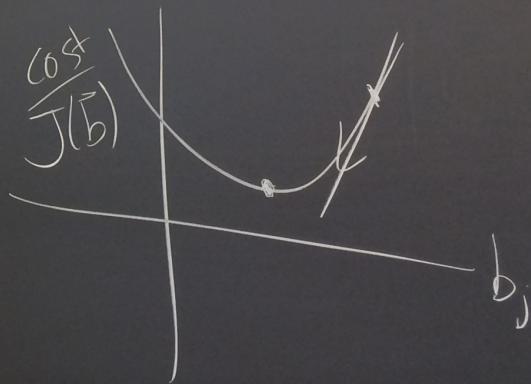
$$= \left[-y_i + \cancel{y_i h_b(\bar{x}_i)} + h_b(\bar{x}_i) - \cancel{y_i h_b(\bar{x}_i)} \right] (+x_{ij})$$

$$\rightarrow (h_b(\bar{x}_i) - y_i)(+x_{ij})$$

SGD

same as
linear
regression!

$$b_j \leftarrow b_j - \alpha (h_b(\bar{x}_i) - y_i) x_{ij}$$



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Multi-class Logistic Regression

- political party
- blood groups

K classes

$$y \in \{1, 2, \dots, K\}$$

$$h_b(\vec{x}) = \frac{1}{1 + e^{-\vec{b}^T \vec{x}}}$$

$$h_b(\vec{x}) = \frac{e^{\vec{b}^T \vec{x}}}{\underbrace{e^{\vec{b}^T \vec{x}}}_{\text{weight on class } y=1} + \underbrace{1}_{\text{weight on class } y=0}}$$

$$\underbrace{1 - h_b(\vec{x})}_{\text{prob } y=0} = \frac{1}{e^{\vec{b}^T \vec{x}} + 1}$$

$$h_B(\vec{x}) = \begin{bmatrix} p(y=1|\vec{x}) \\ p(y=2|\vec{x}) \\ \vdots \\ p(y=K|\vec{x}) \end{bmatrix}$$

must sum to 1

$$= \frac{1}{\sum_{k=1}^K e^{\vec{b}^{(k)T} \vec{x}}} \begin{bmatrix} e^{\vec{b}^{(1)T} \vec{x}} \\ e^{\vec{b}^{(2)T} \vec{x}} \\ \vdots \\ e^{\vec{b}^{(K)T} \vec{x}} \end{bmatrix}$$

normalizer

$$B = \begin{bmatrix} 1 & 1 & 1 \\ \vec{b}^{(1)} & \vec{b}^{(2)} & \vdots \\ 1 & 1 & 1 \end{bmatrix}$$

$(p+1) \times K$

cost function

$$J_B(\vec{x}) = \sum_{i=1}^n \sum_{k=1}^K \underbrace{1(y_i=k)}_{\text{indicator}} \underbrace{\log p(y_i=k | \vec{x}_i)}_{\text{cost of class } k}$$

K

indicator
if true $\Rightarrow 1$
else $\Rightarrow 0$

cost of
class k