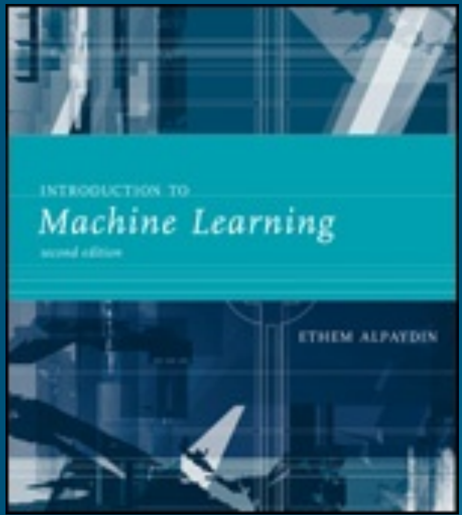

Lecture Slides for

INTRODUCTION TO

Machine Learning

2nd Edition

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In preparation of these slides, I have benefited from slides prepared by:

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D. Bouchaffra and V. Murino (Pattern Classification and Scene Analysis),

R. Gutierrez-Osuna (Texas A&M)

A. Moore (CMU)

CHAPTER 4:

Parametric Methods

Parametric Estimation

- $\mathcal{X} = \{ x^t \}_t$ where $x^t \sim p(x)$
- Parametric estimation:

  Assume a form for $p(x \mid \theta)$ and estimate θ, its sufficient statistics, using X

  e.g., N (μ, σ^2) where $\theta = \{ \mu, \sigma^2 \}$

Maximum Likelihood Estimation

- Likelihood of θ given the sample $\mathcal{X}$

  $$l(\theta|\mathcal{X}) = p(\mathcal{X}|\theta) = \prod_t p(x^t|\theta)$$

- Log likelihood

  $$\mathcal{L}(\theta|\mathcal{X}) = \log l(\theta|\mathcal{X}) = \sum_t \log p(x^t|\theta)$$

- Maximum likelihood estimator (MLE)

  $$\theta^* = \text{argmax}_\theta\ \mathcal{L}(\theta|\mathcal{X})$$

Examples: Bernoulli/Multinomial

- Bernoulli: Two states, failure/success, *x* in {0,1}

  $P(x) = p_o^{x}(1 - p_o)^{(1-x)}$

  $\mathcal{L}(p_o|\mathcal{X}) = \log \prod_t p_o^{x^t}(1 - p_o)^{(1-x^t)}$

  MLE: $p_o = \sum_t x^t / N$

- Multinomial: K>2 states, x_i in {0,1}

  $P(x_1, x_2, \ldots, x_K) = \prod_i p_i^{x_i}$

  $\mathcal{L}(p_1, p_2, \ldots, p_K|\mathcal{X}) = \log \prod_t \prod_i p_i^{x_i^t}$

  MLE: $p_i = \sum_t x_i^t / N$

Examples: Bernoulli (Derivation)

- Bernoulli: Two states, failure/success, x in {0,1}

  $P(x) = p_o^{x}(1 - p_o)^{(1 - x)}$

  $\mathcal{L}(p_o|\mathcal{X}) = \log \Pi_t\, p_o^{x^t}(1 - p_o)^{(1 - x^t)}$

$$\frac{dL(p_0 \mid X)}{dp_0} = \sum_{t=1}^{N} x^t \frac{d}{dp_0}\log(p_0) + \sum_{t=1}^{N}(1 - x^t)\frac{d}{dp_0}\log(1 - p_0)$$

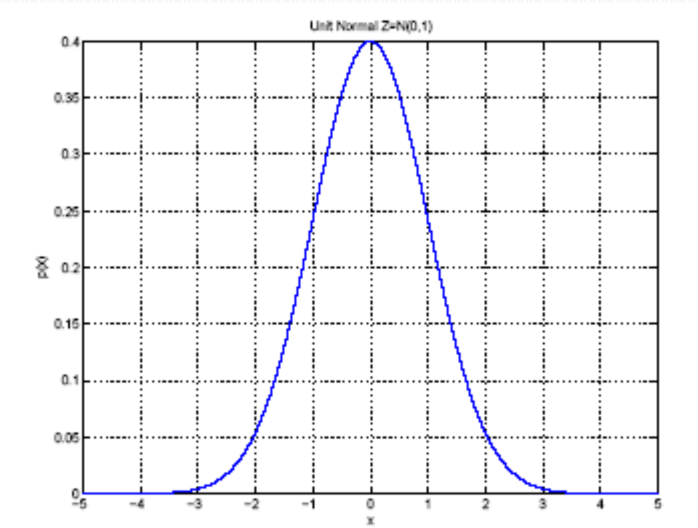
$$= \frac{1}{p_0}\sum_{t=1}^{N} x^t - \sum_{t=1}^{N}(1 - x^t)\frac{1}{1 - p_0} = 0$$

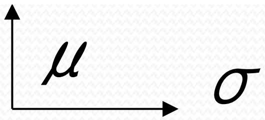
$$= (1 - p_0)\sum_{t=1}^{N} x^t - p_0\sum_{t=1}^{N} 1 + p_0\sum_{t=1}^{N} x^t = 0$$

$$= \sum_{t=1}^{N} x^t - p_0 N = 0 \Rightarrow p_0 = \frac{1}{N}\sum_{t=1}^{N} x^t$$

MLE: $p_o = \Sigma_t\, x^t / N$

Gaussian (Normal) Distribution





- $p(x) = \mathcal{N}(\mu, \sigma^2)$

$$p(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{(x-\mu)^2}{2\sigma^2}\right]$$

- MLE for μ and σ^2:

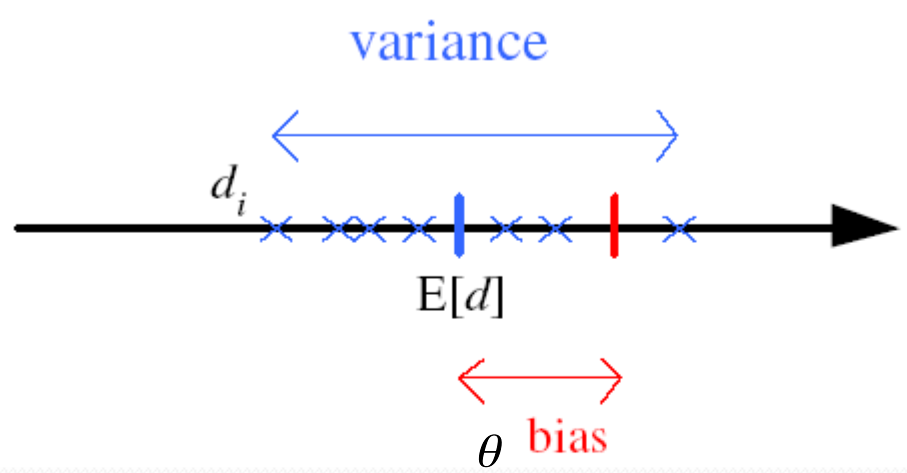
$$m = \frac{\sum_t x^t}{N}$$

$$s^2 = \frac{\sum_t (x^t - m)^2}{N}$$

Bias and Variance

Unknown parameter θ
Estimator $d_i = d(X_i)$ on sample X_i

Bias: $b_\theta(d) = E[d] - \theta$
Variance: $E[(d - E[d])^2]$



Mean square error:

$r(d,\theta) = E[(d-q)^2] = E[(d-E[d]+E[d]-\Theta)^2]$

$= (E[d]-\theta)^2 + E[(d-E[d])^2 + 2(d-E[d])(E[d]-\theta)]$

$= E[(E[d]-\theta)^2] + E[(d-E[d])^2] + 2E[(d-E[d])(E[d]-\theta)]$

$= E[(E[d]-\theta)^2] + E[(d-E[d])^2] + 2(E[d]-E[d])(E[d]-\theta)$

$= (E[d]-\theta)^2 + E[(d-E[d]^{)2}]$

$= (E[d]-\Theta)^2 + E[(d-E[d])^2]$

$=$ Bias^2 + Variance

Remember the properties of expectation

Bayes' Estimator

- Treat θ as a random var with prior $p(\theta)$
- Bayes' rule: $p(\theta|\mathcal{X}) = p(\mathcal{X}|\theta)\, p(\theta) \,/\, p(\mathcal{X})$
- Full: $p(x|\mathcal{X}) = \int p(x|\theta)\, p(\theta|\mathcal{X})\, d\theta$
- Maximum a Posteriori (MAP): $\theta_{\text{MAP}} = \text{argmax}_\theta\, p(\theta|\mathcal{X})$
- Maximum Likelihood (ML): $\theta_{\text{ML}} = \text{argmax}_\theta\, p(\mathcal{X}|\theta)$
- Bayes': $\theta_{\text{Bayes'}} = \mathrm{E}[\theta|\mathcal{X}] = \int \theta\, p(\theta|\mathcal{X})\, d\theta$

Bayes' Estimator: Example

- $x^t \sim \mathcal{N}(\theta, \sigma_o^2)$ and $\theta \sim \mathcal{N}(\mu, \sigma^2)$
- $\theta_{\mathrm{ML}} = m$
- $\theta_{\mathrm{MAP}} = \theta_{\mathrm{Bayes'}} =$

$$E[\theta \mid \mathcal{X}] = \frac{N/\sigma_0^2}{N/\sigma_0^2 + 1/\sigma^2} m + \frac{1/\sigma^2}{N/\sigma_0^2 + 1/\sigma^2} \mu$$

Parametric Classification

$$g_i(x) = p(x \mid C_i)P(C_i)$$

or

$$g_i(x) = \log p(x \mid C_i) + \log P(C_i)$$

$$p(x \mid C_i) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left[-\frac{(x-\mu_i)^2}{2\sigma_i^2}\right]$$

$$g_i(x) = -\frac{1}{2}\log 2\pi - \log \sigma_i - \frac{(x-\mu_i)^2}{2\sigma_i^2} + \log P(C_i)$$

- Given the sample $\mathcal{X} = \{x^t, r^t\}_{t=1}^{N}$

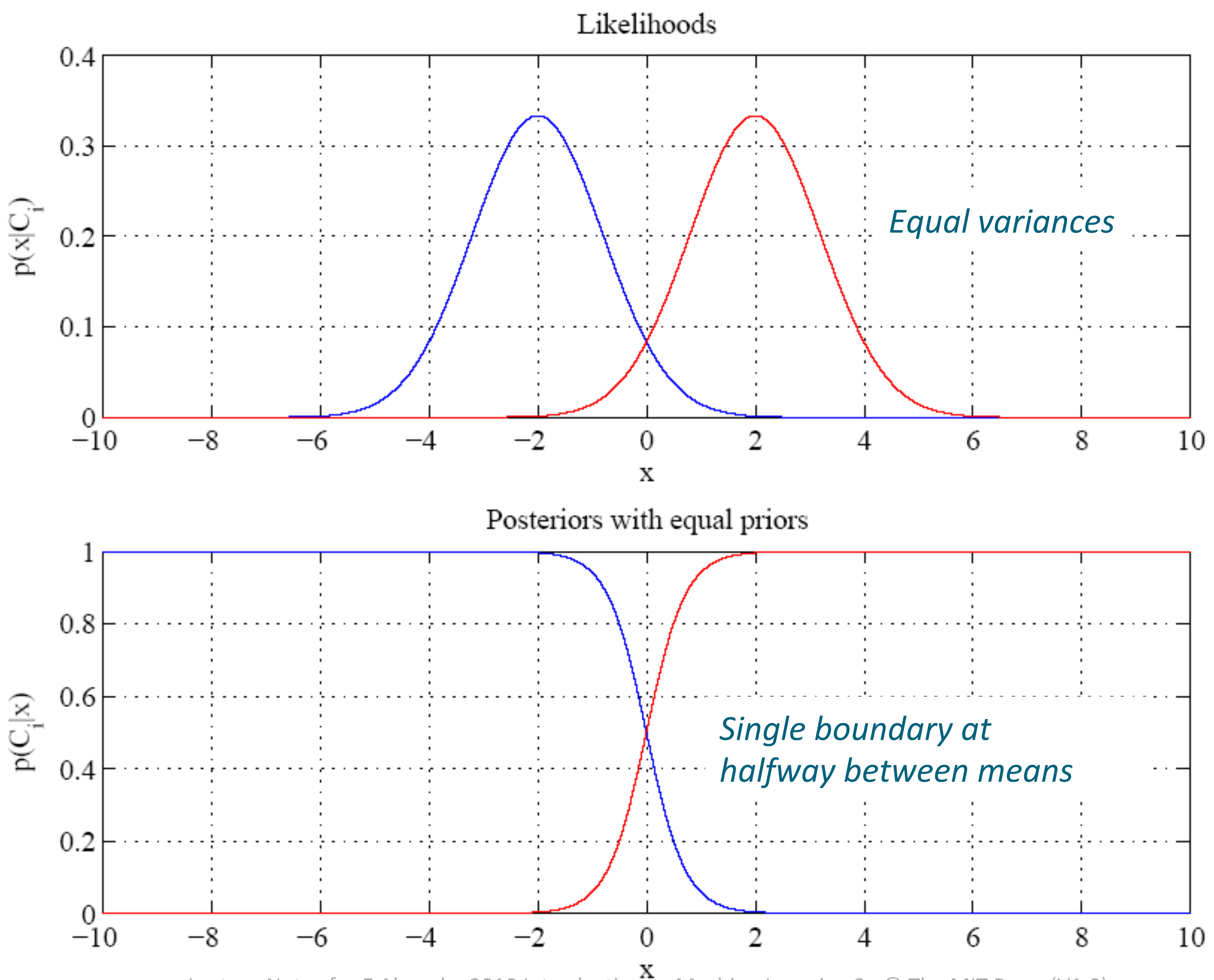
$$x \in \Re \qquad r_i^t = \begin{cases} 1 \text{ if } x^t \in C_i \\ 0 \text{ if } x^t \in C_j, j \neq i \end{cases}$$

- ML estimates are

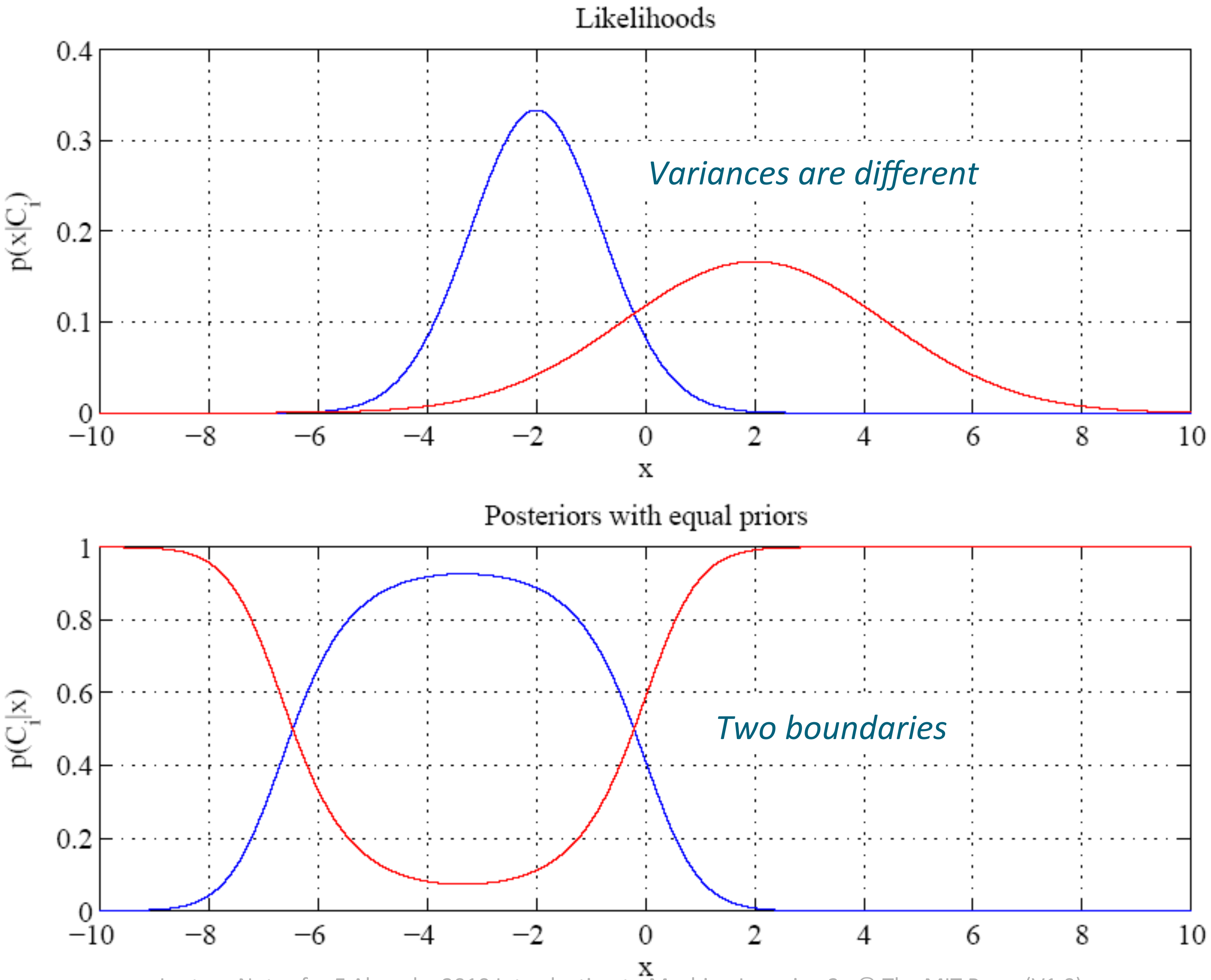
$$\hat{P}(C_i) = \frac{\sum_t r_i^t}{N} \quad m_i = \frac{\sum_t x^t r_i^t}{\sum_t r_i^t} \quad s_i^2 = \frac{\sum_t (x^t - m_i)^2 r_i^t}{\sum_t r_i^t}$$

- Discriminant becomes

$$g_i(x) = -\frac{1}{2}\log 2\pi - \log s_i - \frac{(x - m_i)^2}{2s_i^{\,2}} + \log \hat{P}(C_i)$$



Likelihoods
p(x|C_i)
x
Equal variances
Posteriors with equal priors
p(C_i|x)
x
Single boundary at
halfway between means


Likelihoods
Variances are different
p(x|C_i)
x
Posteriors with equal priors
Two boundaries
p(C_i|x)
x

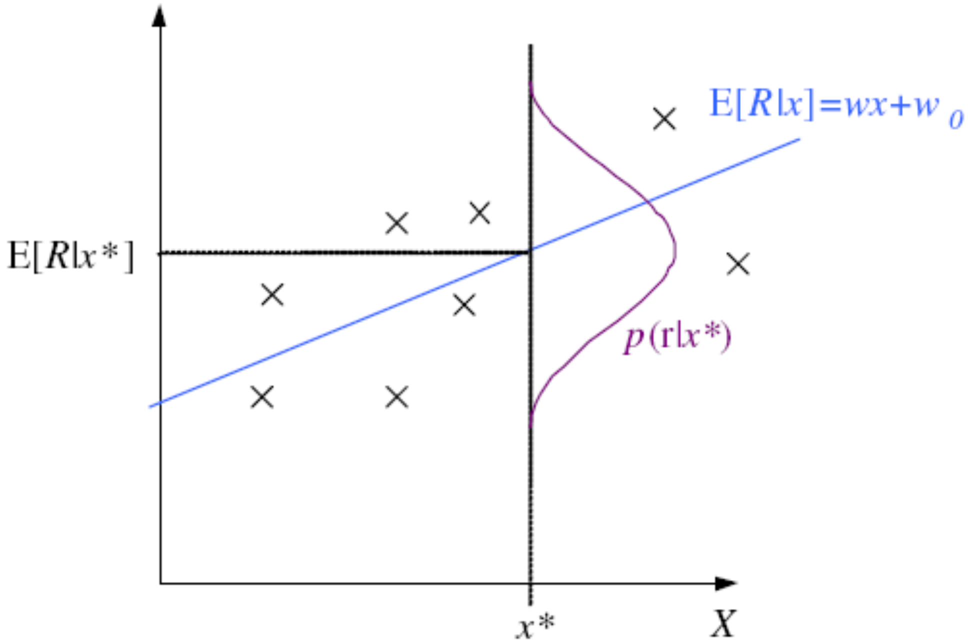
Regression

$$r = f(x) + \varepsilon$$

$$\text{estimator}: g(x \mid \theta)$$

$$\varepsilon \sim \mathcal{N}(0, \sigma^2)$$

$$p(r \mid x) \sim \mathcal{N}(g(x \mid \theta), \sigma^2)$$



$$\mathcal{L}(\theta \mid \mathcal{X}) = \log \prod_{t=1}^{N} p(x^t, r^t)$$

$$= \log \prod_{t=1}^{N} p(r^t \mid x^t) + \log \prod_{t=1}^{N} p(x^t)$$

Regression: From LogL to Error

$$\mathcal{L}(\theta|\mathcal{X}) = \log \prod_{t=1}^{N} \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{\left[r^t - g\left(x^t|\theta\right)\right]^2}{2\sigma^2}\right]$$

$$= -N \log\sqrt{2\pi}\sigma - \frac{1}{2\sigma^2}\sum_{t=1}^{N}\left[r^t - g\left(x^t|\theta\right)\right]^2$$

$$E(\theta|\mathcal{X}) = \frac{1}{2}\sum_{t=1}^{N}\left[r^t - g\left(x^t|\theta\right)\right]^2$$

Linear Regression

$$E(\theta|\mathcal{X}) = \frac{1}{2}\sum_{t=1}^{N}\left[r^t - g\left(x^t|\theta\right)\right]$$

$$g\left(x^t | w_1, w_0\right) = w_1 x^t + w_0$$

Take derivative of E

$$\sum_t r^t = N w_0 + w_1 \sum_t x^t$$

...wrto w0

$$\sum_t r^t x^t = w_0 \sum_t x^t + w_1 \sum_t \left(x^t\right)^2$$

...wrto w1

$$\mathbf{A} = \begin{bmatrix} N & \sum_t x^t \\ \sum_t x^t & \sum_t \left(x^t\right)^2 \end{bmatrix} \quad \mathbf{w} = \begin{bmatrix} w_0 \\ w_1 \end{bmatrix} \quad \mathbf{y} = \begin{bmatrix} \sum_t r^t \\ \sum_t r^t x^t \end{bmatrix}$$

$$\mathbf{w} = \mathbf{A}^{-1}\mathbf{y}$$

Polynomial Regression

$$g\left(x^t \mid w_k, \ldots, w_2, w_1, w_0\right) = w_k \left(x^t\right)^k + \cdots + w_2 \left(x^t\right)^2 + w_1 x^t + w_0$$

$$\mathbf{D} = \begin{bmatrix} 1 & x^1 & \left(x^1\right)^2 & \cdots & \left(x^1\right)^k \\ 1 & x^2 & \left(x^2\right)^2 & \cdots & \left(x^2\right)^k \\ \vdots & & & & \\ 1 & x^N & \left(x^N\right)^2 & \cdots & \left(x^N\right)^2 \end{bmatrix} \quad \mathbf{r} = \begin{bmatrix} r^1 \\ r^2 \\ \vdots \\ r^N \end{bmatrix}$$

$$\mathbf{w} = \left(\mathbf{D}^T \mathbf{D}\right)^{-1} \mathbf{D}^T \mathbf{r}$$

Other Error Measures

- Square Error: $$E(\theta|\mathcal{X}) = \frac{1}{2}\sum_{t=1}^{N}\left[r^t - g(x^t|\theta)\right]^2$$
- Relative Square Error: $$E(\theta|\mathcal{X}) = \frac{\sum_{t=1}^{N}\left[r^t - g(x^t|\theta)\right]^2}{\sum_{t=1}^{N}\left[r^t - \bar{r}\right]^2}$$
- Absolute Error: $E(\theta|X) = \sum_t |r^t - g(x^t|\theta)|$
- ε-sensitive Error:

$$E(\theta|X) = \sum_t 1(|r^t - g(x^t|\theta)| > \varepsilon)\,(|r^t - g(x^t|\vartheta)| - \varepsilon)$$

Bias and Variance

$$E\left[(r-g(x))^2 \mid x\right] = E\left[(r-E[r \mid x])^2 \mid x\right] + (E[r \mid x] - g(x))^2$$

noise *squared error*

$$E_{\mathcal{X}}\left[(E[r \mid x] - g(x))^2 \mid x\right] = (E[r \mid x] - E_{\mathcal{X}}[g(x)])^2 + E_{\mathcal{X}}\left[(g(x) - E_{\mathcal{X}}[g(x)])^2\right]$$

bias *variance*

Estimating Bias and Variance

- M samples $X_i=\{x^t_i, r^t_i\}$, $i=1,\ldots,M$
  are used to fit $g_i(x)$, $i=1,\ldots,M$

$$\text{Bias}^2(g)=\frac{1}{N}\sum_t\left[\bar{g}\left(x^t\right)-f\left(x^t\right)\right]^2$$

$$\text{Variance}(g)=\frac{1}{NM}\sum_t\sum_i\left[g_i\left(x^t\right)-\bar{g}\left(x^t\right)\right]^2$$

$$\bar{g}(x)=\frac{1}{M}\sum_t g_i(x)$$

Bias/Variance Dilemma

- Example: $g_i(x)=2$ has no variance and high bias

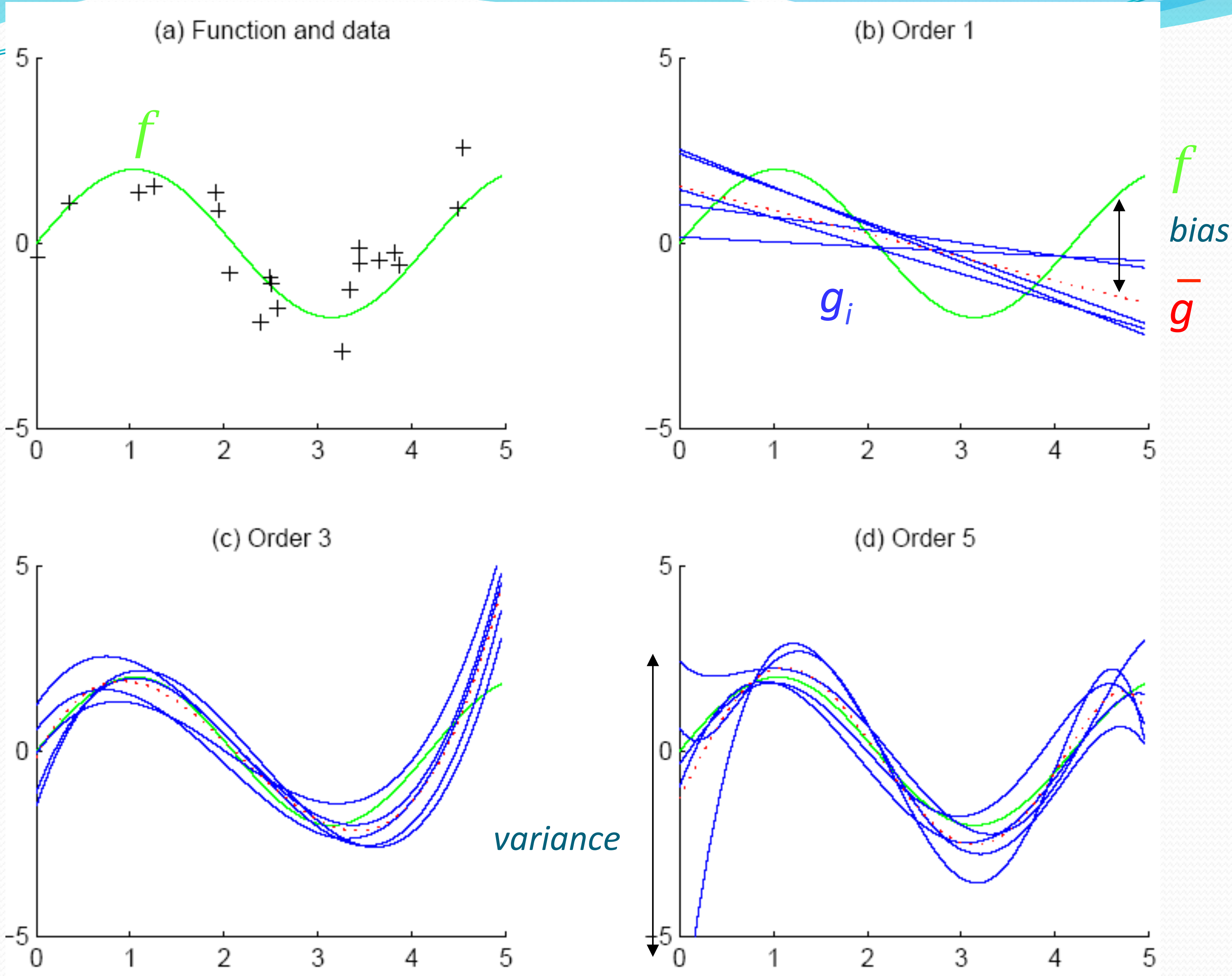
  $g_i(x)= \sum_t r^t_i/N$ has lower bias with variance

- As we increase complexity,

  bias decreases (a better fit to data) and

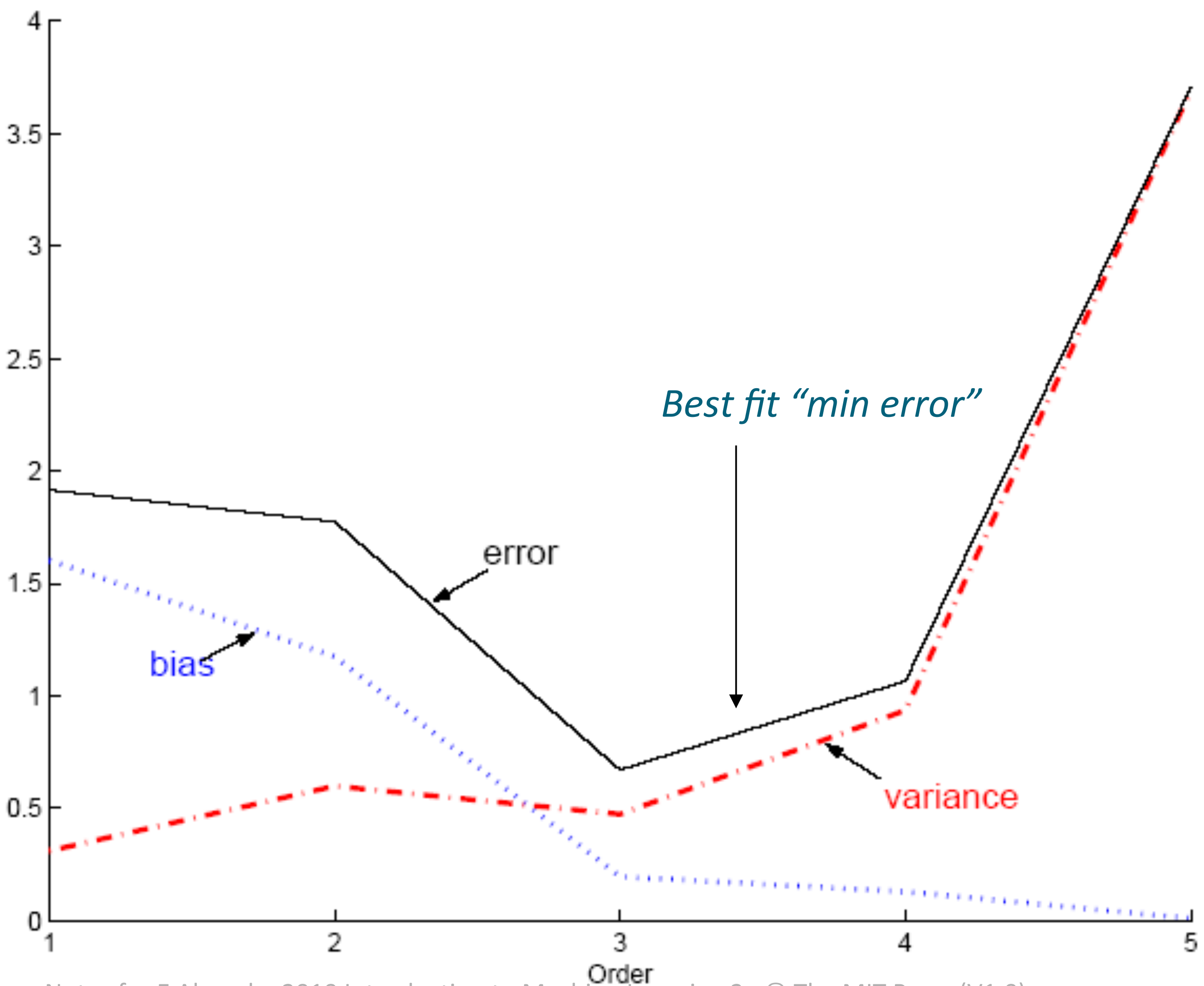
  variance increases (fit varies more with data)

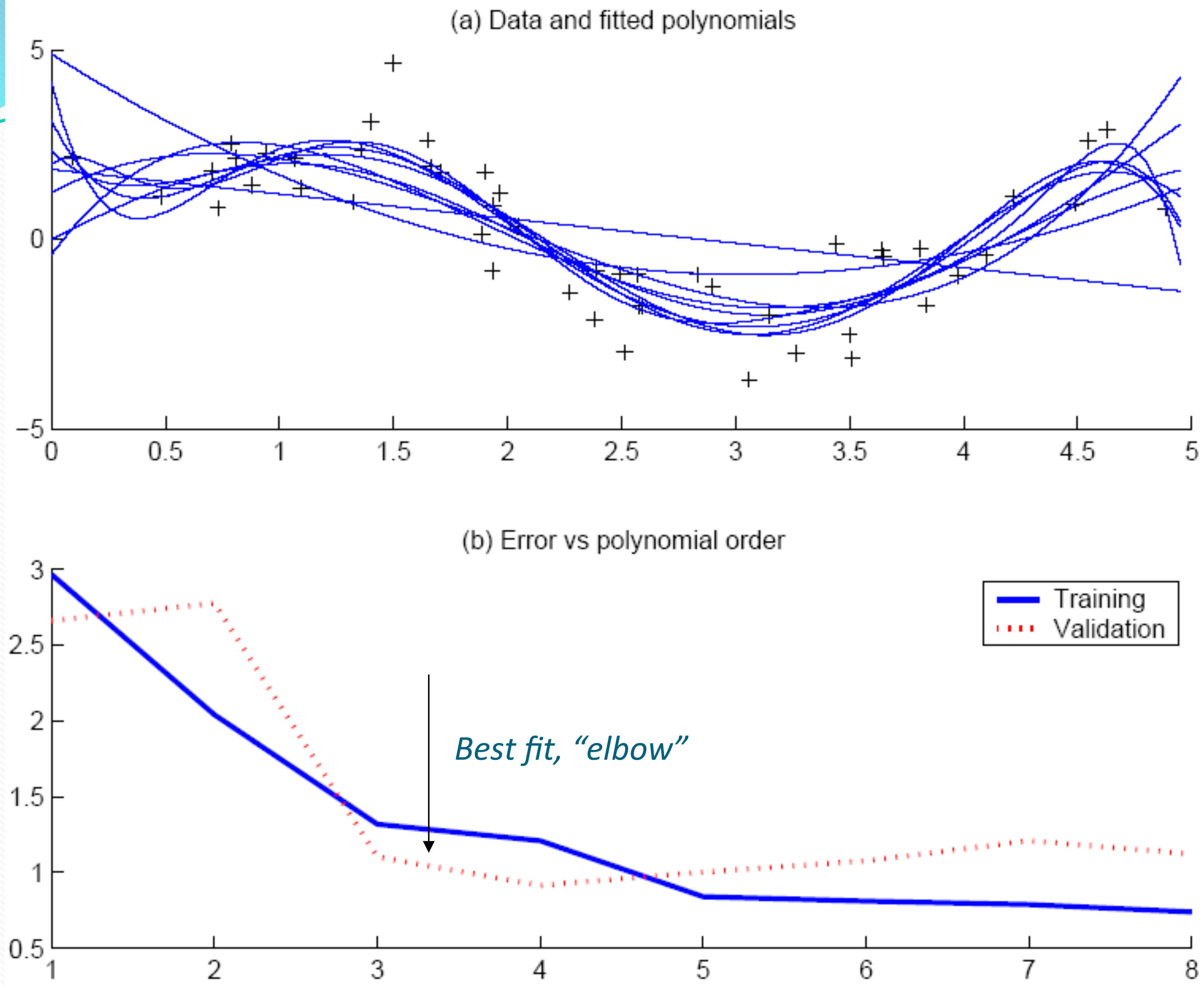
- Bias/Variance dilemma: (Geman et al., 1992)



(a) Function and data
f
(b) Order 1
f
bias
g_i
$\bar{g}$
(c) Order 3
variance
(d) Order 5

Polynomial Regression




(a) Data and fitted polynomials
5
0
−5
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
(b) Error vs polynomial order
Training
Validation
Best fit, “elbow”
3
2.5
2
1.5
1
0.5
1
2
3
4
5
6
7
8

Model Selection

- Cross-validation: Measure generalization accuracy by testing on data unused during training
- Regularization: Penalize complex models

  E'=error on data + λ model complexity

  Akaike's information criterion (AIC), Bayesian information criterion (BIC)
- Minimum description length (MDL): Kolmogorov complexity, shortest description of data
- Structural risk minimization (SRM)

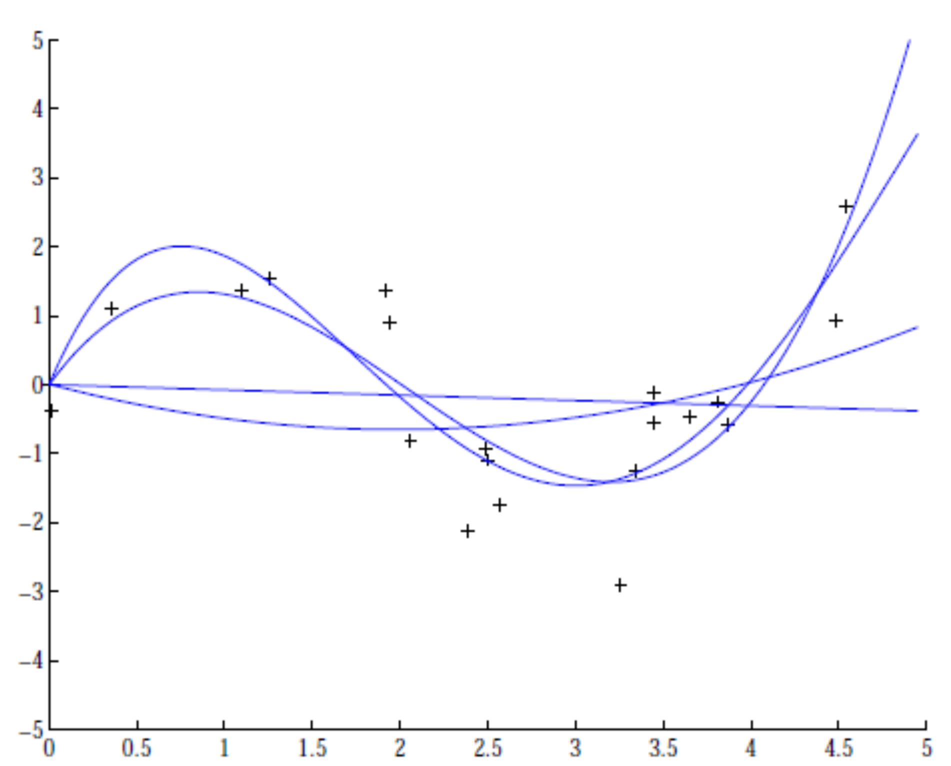
Bayesian Model Selection

- Prior on models, $p(\text{model})$

$$p(\text{model} \mid \text{data}) = \frac{p(\text{data} \mid \text{model})\, p(\text{model})}{p(\text{data})}$$

- Regularization, when prior favors simpler models
- Bayes, MAP of the posterior, $p(\text{model}|\text{data})$
- Average over a number of models with high posterior (voting, ensembles: Chapter 17)

Regression example



Coefficients increase in magnitude as order increases:

1: [-0.0769, 0.0016]

2: [0.1682, -0.6657, 0.0080]

3: [0.4238, -2.5778, 3.4675, -0.0002

4: [-0.1093, 1.4356, -5.5007, 6.0454, -0.0019]

$$regularization: E(\mathbf{w} \mid \mathcal{X}) = \frac{1}{2}\sum_{t=1}^{N}\left[r^t - g\left(x^t \mid \mathbf{w}\right)\right]^2 + \lambda \sum_i w_i^2$$