

Machine Learning

Lecture 4: Linear Regression

Prof. Dr. Stephan Günnemann

Data Analytics and Machine Learning
Technical University of Munich

Winter term 2022/2023

Notation

Symbol	Meaning
x	scalar is lowercase and not bold
\boldsymbol{x}	vector is lowercase and bold
Σ	matrix is uppercase and bold
$f(\boldsymbol{x})$	predicted value for inputs \boldsymbol{x}
\boldsymbol{y}	vector of targets
y_i	target of the i 'th example
w_0	bias term (not to be confused with bias in general)
$\phi(\cdot)$	basis function
$E(\cdot)$	error function
\mathcal{D}	training data
\boldsymbol{X}^\dagger	Moore-Penrose pseudoinverse of \boldsymbol{X}

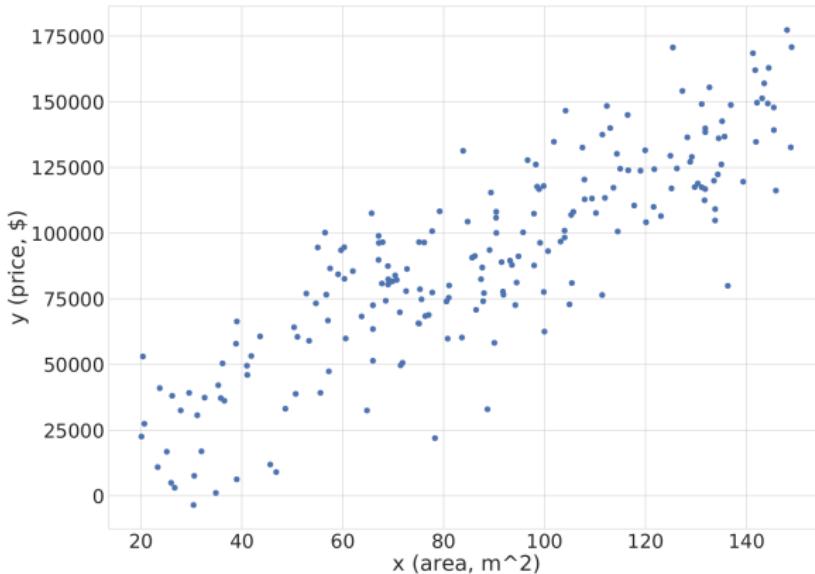
There is not a special symbol for vectors or matrices augmented by the bias term, w_0 . Assume it is always included.

Section 1

Basic Linear Regression

Example: Housing price prediction

Given is a dataset $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^N$, of house areas x_i and corresponding prices y_i .



How do we estimate a price of a new house with area x_{new} ?

Regression problem

Given

- observations ¹

$$\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N\}, \mathbf{x}_i \in \mathbb{R}^D$$

- targets

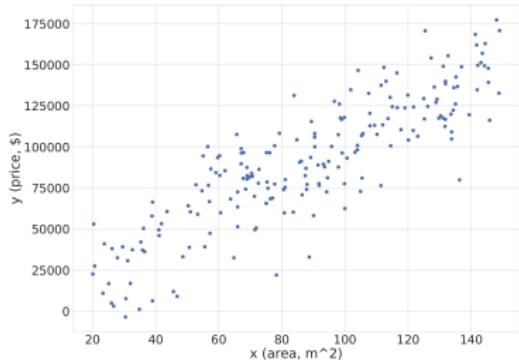
$$\mathbf{y} = \{y_1, y_2, \dots, y_N\}, y_i \in \mathbb{R}$$

Find

- Mapping $f(\cdot)$ from inputs to targets

$$y_i \approx f(\mathbf{x}_i)$$

Linear Model



¹A common way to represent the samples is as a **data matrix** $\mathbf{X} \in \mathbb{R}^{N \times D}$, where each row represents one sample.

Linear model

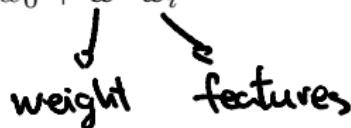
Target y is generated by a deterministic function f of x plus noise

$$y_i = f(\mathbf{x}_i) + \epsilon_i, \quad \epsilon_i \sim \mathcal{N}(0, \beta^{-1}) \quad (1)$$

Let's choose $f(x)$ to be a linear function

$$f_{\mathbf{w}}(\mathbf{x}_i) = w_0 + w_1 x_{i1} + w_2 x_{i2} + \dots + w_D x_{iD} \quad (2)$$

$$= w_0 + \mathbf{w}^T \mathbf{x}_i \quad (3)$$


weight features

From now we will always assume that the bias term is absorbed into the \mathbf{x} vector

Absorbing the bias term

$$x = \begin{bmatrix} 2 \\ 5 \end{bmatrix} \quad \tilde{x} = \begin{bmatrix} 1 \\ 2 \\ 5 \end{bmatrix}$$

The linear function is given by

$$f_w(x) = w_0 + w_1 x_1 + w_2 x_2 + \dots + w_D x_D \quad (4)$$

$$= w_0 + \mathbf{w}^T \mathbf{x} \quad (5)$$

Here w_0 is called **bias or offset** term. For simplicity, we can "absorb" it by prepending a 1 to the feature vector x and respectively adding w_0 to the weight vector w :

$$\tilde{x} = (1, x_1, \dots, x_D)^T \quad \tilde{w} = (w_0, w_1, \dots, w_D)^T$$

$\tilde{x} \in \mathbb{R}^{D+1}$ *$\tilde{w} \in \mathbb{R}^{D+1}$*

The function f_w can compactly be written as $f_w(x) = \tilde{w}^T \tilde{x}$.

To unclutter the notation, we will assume the bias term is always absorbed and write w and x instead of \tilde{w} and \tilde{x} .

Now, how do we choose the "best" w that fits our data?

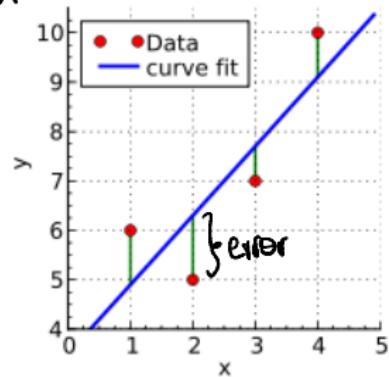
Loss function

A **loss function** measures the “misfit” or error between our model (parametrized by w) and observed data $\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^N$.

Standard choice - **least squares** (LS)

$$E_{\text{LS}}(\mathbf{w}) = \frac{1}{2} \sum_{i=1}^N (f_{\mathbf{w}}(\mathbf{x}_i) - y_i)^2 \quad (6)$$

$$= \frac{1}{2} \sum_{i=1}^N (\mathbf{w}^T \mathbf{x}_i - y_i)^2 \quad (7)$$



Factor $\frac{1}{2}$ is for later convenience

Objective

Find the optimal weight vector \mathbf{w}^* that minimizes the error

$$\mathbf{w}^* = \arg \min_{\mathbf{w}} E_{\text{LS}}(\mathbf{w}) \quad (8)$$

$$= \arg \min_{\mathbf{w}} \frac{1}{2} \sum_{i=1}^N (\mathbf{x}_i^T \mathbf{w} - y_i)^2 \quad (9)$$

By stacking the observations \mathbf{x}_i as rows of the matrix $\mathbf{X} \in \mathbb{R}^{N \times D}$

$$= \arg \min_{\mathbf{w}} \frac{1}{2} (\mathbf{X}\mathbf{w} - \mathbf{y})^T (\mathbf{X}\mathbf{w} - \mathbf{y}) \quad (10)$$

$$\begin{matrix} & & \\ & \nearrow & \nearrow & \nearrow \\ \mathbf{e} \mathbb{R}^{N \times D} & \mathbf{e} \mathbb{R}^{D \times 1} & \mathbf{e} \mathbb{R}^{N \times 1} \end{matrix}$$

Optimal solution

To find the minimum of the loss $E(\mathbf{w})$, compute the gradient $\nabla_{\mathbf{w}}E(\mathbf{w})$:

$$\nabla_{\mathbf{w}}E_{\text{LS}}(\mathbf{w}) = \nabla_{\mathbf{w}} \frac{1}{2} (\mathbf{X}\mathbf{w} - \mathbf{y})^T (\mathbf{X}\mathbf{w} - \mathbf{y}) \quad (11)$$

$$= \nabla_{\mathbf{w}} \frac{1}{2} \left(\mathbf{w}^T \mathbf{X}^T \mathbf{X} \mathbf{w} - 2\mathbf{w}^T \mathbf{X}^T \mathbf{y} + \mathbf{y}^T \mathbf{y} \right) \quad (12)$$

$$= \mathbf{X}^T \mathbf{X} \mathbf{w} - \mathbf{X}^T \mathbf{y} \quad (13)$$

See Equations (69), (81) from Matrix cookbook for details

Optimal solution

Now set the gradient to zero and solve for w to obtain the minimizer²

$$X^T X w - X^T y \stackrel{!}{=} 0 \quad \begin{array}{l} \text{set it to 0} \\ \text{to find the minimum} \end{array} \quad (14)$$

This leads to the so-called **normal equation** of the least squares problem

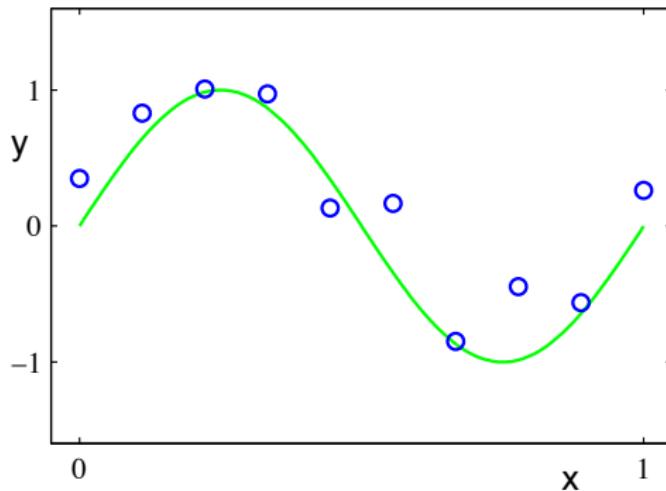
$$w^* = \underbrace{(X^T X)^{-1} X^T y}_{=X^\dagger} \quad (15)$$

X^\dagger is called **Moore-Penrose pseudo-inverse** of X (because for an invertible square matrix, $X^\dagger = X^{-1}$).

²Because Hessian $\nabla_w \nabla_w E(w)$ is positive (semi)definite → see *Optimization*

Nonlinear dependency in data

What if the dependency between y and x is not linear?



Data generating process: $y_i = \sin(2\pi x_i) + \epsilon_i, \quad \epsilon_i \sim \mathcal{N}(0, \beta^{-1})$

For this example assume that the data dimensionality is $D = 1$

Polynomials

Solution: Polynomials are universal function approximators, so for 1-dimensional x we can define f as

$$f_w(x) = w_0 + \sum_{j=1}^M w_j x^j \quad (16)$$

degree of the polynomial

Or more generally

$$\text{Ex.: } \phi_1(x) = \sqrt{x}$$
$$= w_0 + \sum_{j=1}^M w_j \phi_j(x) \quad (17)$$

Define $\phi_0 = 1$

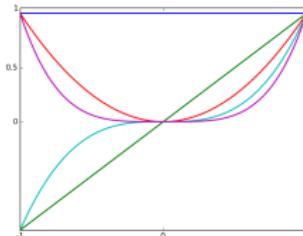
$$= \mathbf{w}^T \phi(x) \quad (18)$$

The function f is still linear in \mathbf{w} (despite not being linear in x)!

Typical basis functions

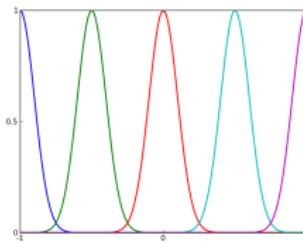
Polynomials

$$\phi_j(x) = x^j$$



Gaussian

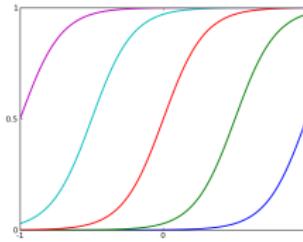
$$\phi_j(x) = e^{\frac{-(x-\mu_j)^2}{2s^2}}$$



Logistic Sigmoid

$$\phi_j(x) = \sigma\left(\frac{x-\mu_j}{s}\right),$$

$$\text{where } \sigma(a) = \frac{1}{1+e^{-a}}$$



Linear basis function model

For d -dimensional data \mathbf{x} : $\phi_j : \mathbb{R}^d \rightarrow \mathbb{R}$

Prediction for one sample

$$f_{\mathbf{w}}(\mathbf{x}) = w_0 + \sum_{j=1}^M w_j \phi_j(\mathbf{x}) = \mathbf{w}^T \phi(\mathbf{x}) \quad (19)$$

Using the same least squares error function as before

$$E_{\text{LS}}(\mathbf{w}) = \frac{1}{2} \sum_{i=1}^N (\mathbf{w}^T \phi(\mathbf{x}_i) - y_i)^2 = \frac{1}{2} (\Phi \mathbf{w} - \mathbf{y})^T (\Phi \mathbf{w} - \mathbf{y}) \quad (20)$$

with

$$\Phi = \begin{pmatrix} \phi_0(\mathbf{x}_1) & \phi_1(\mathbf{x}_1) & \dots & \phi_M(\mathbf{x}_1) \\ \phi_0(\mathbf{x}_2) & \phi_1(\mathbf{x}_2) & & \vdots \\ \vdots & \vdots & \ddots & \\ \phi_0(\mathbf{x}_N) & \phi_1(\mathbf{x}_N) & \dots & \phi_M(\mathbf{x}_N) \end{pmatrix} \in \mathbb{R}^{N \times (M+1)}$$

being the **design matrix** of ϕ .

Optimal solution

Recall the final form of the least squares loss that we arrived at for the original feature matrix \mathbf{X}

$$E_{\text{LS}}(\mathbf{w}) = \frac{1}{2}(\mathbf{X}\mathbf{w} - \mathbf{y})^T(\mathbf{X}\mathbf{w} - \mathbf{y})$$

and compare it to the expression we found with the design matrix $\Phi \in \mathbb{R}^{N \times (M+1)}$

$$E_{\text{LS}}(\mathbf{w}) = \frac{1}{2}(\Phi\mathbf{w} - \mathbf{y})^T(\Phi\mathbf{w} - \mathbf{y}). \quad (21)$$

This means that the optimal weights \mathbf{w}^* can be obtained in the same way

$$\mathbf{w}^* = (\Phi^T\Phi)^{-1}\Phi^T\mathbf{y} = \Phi^\dagger\mathbf{y} \quad (22)$$

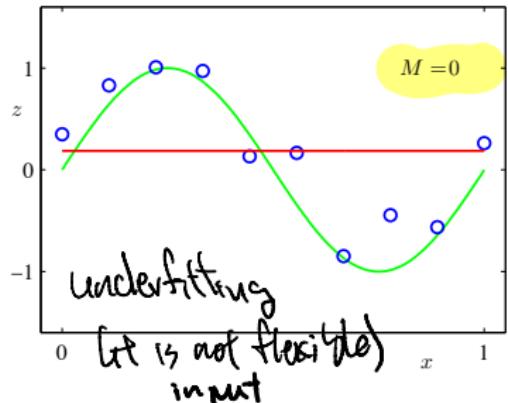
Compare this to Equation 15:

$$\mathbf{w}^* = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y} = \mathbf{X}^\dagger\mathbf{y} \quad (23)$$

Choosing degree of the polynomial

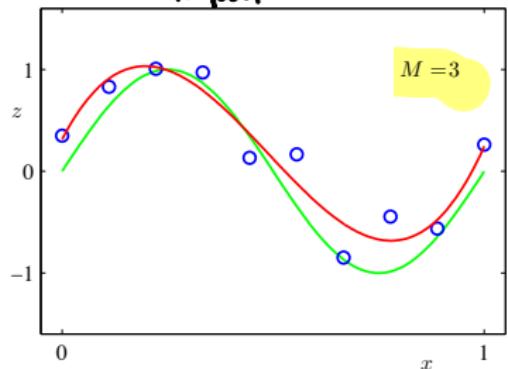
How do we choose the degree of the polynomial M ?

output

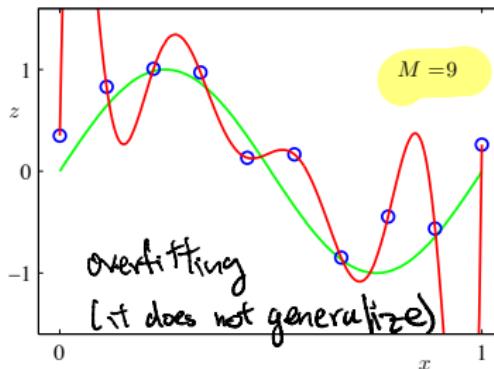
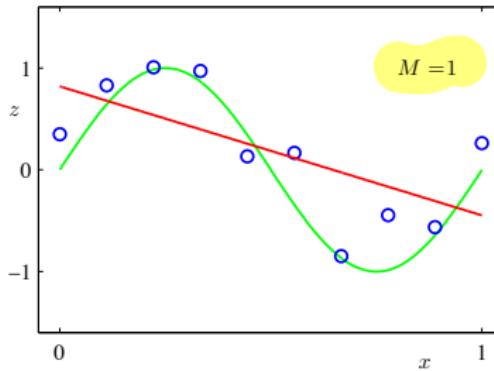


$M = 0$

$M = 1$



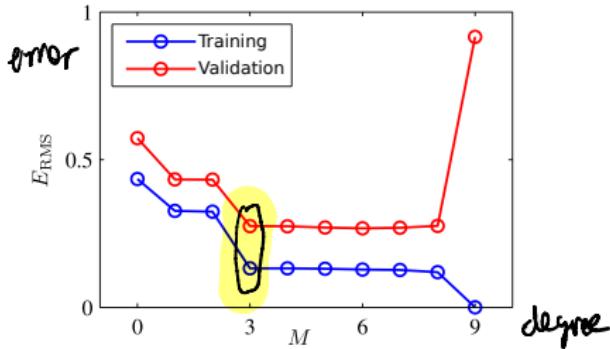
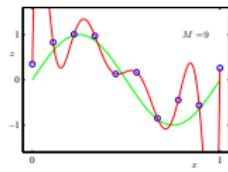
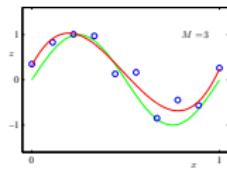
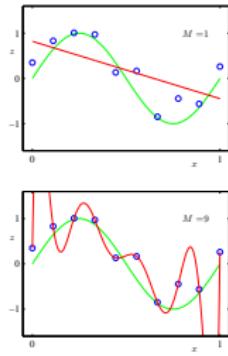
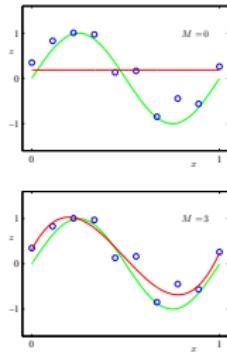
$M = 1$



$M = 3$

$M = 9$

Choosing degree of the polynomial

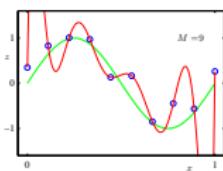
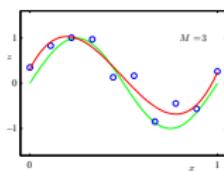
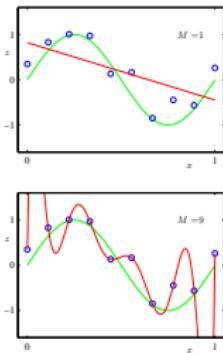
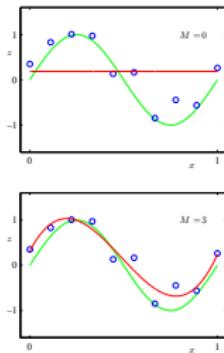


One valid solution is to choose M using the standard train-validation split approach.

Choosing degree of the polynomial

$$M=0 \quad w_0$$

$$M=3 \quad w_0 + w_1 x + w_2 x^2 + w_3 x^3$$



	$M = 0$	$M = 1$	$M = 3$	$M = 9$
w_0^*	0.19	0.82	0.31	0.35
w_1^*		-1.27	7.99	232.37
w_2^*			-25.43	-5321.83
w_3^*				48568.31
w_4^*				-231639.30
w_5^*				640042.26
w_6^*				-1061800.52
w_7^*				1042400.18
w_8^*				-557682.99
w_9^*				125201.43

We also make another observation: overfitting occurs when the coefficients w become large.

What if we penalize large weights?

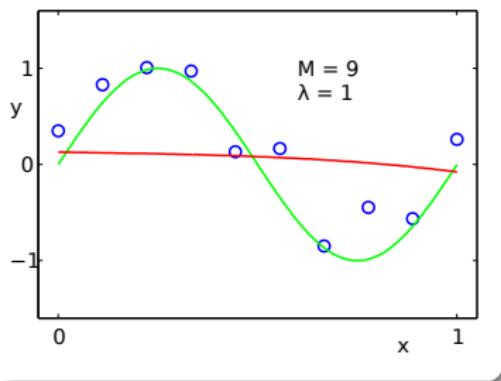
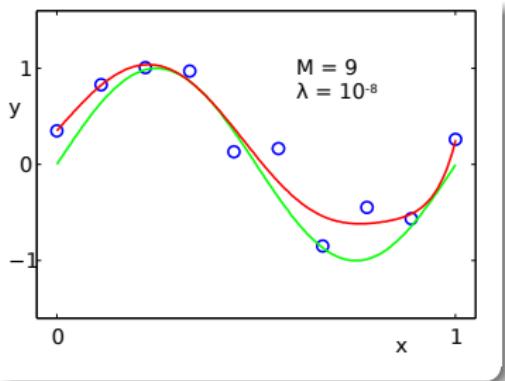
Controlling overfitting with regularization

Least squares loss with L2 regularization (also called ridge regression)

$$E_{\text{ridge}}(\mathbf{w}) = \frac{1}{2} \sum_{i=1}^N [\mathbf{w}^T \phi(\mathbf{x}_i) - y_i]^2 + \frac{\lambda}{2} \|\mathbf{w}\|_2^2 \quad (24)$$

where

- $\|\mathbf{w}\|_2^2 \equiv \mathbf{w}^T \mathbf{w} = w_0^2 + w_1^2 + w_2^2 + \dots + w_M^2$ - squared L2 norm of \mathbf{w}
- λ - regularization strength *penalize large weights*



Larger regularization strength λ leads to smaller weights \mathbf{w}

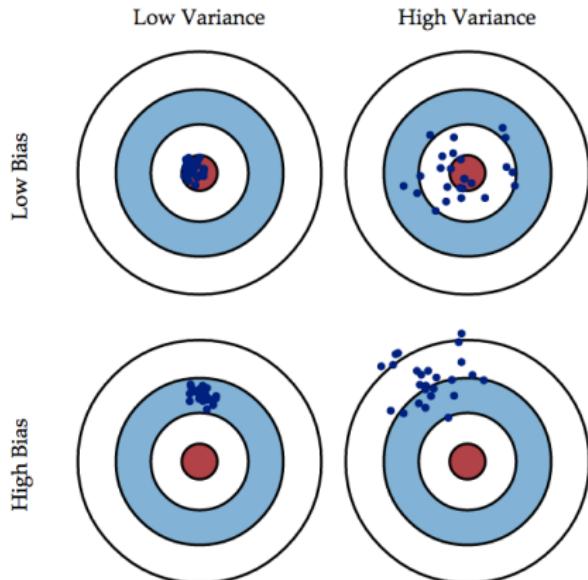
Bias-variance tradeoff

The error of an estimator can be decomposed into two parts:³

- **Bias** - expected error due to model mismatch
- **Variance** - variation due to randomness in training data

the center of the target:
the true model that predicts
the correct values.

different hits (the blue dots):
different realizations of model
given different training data.



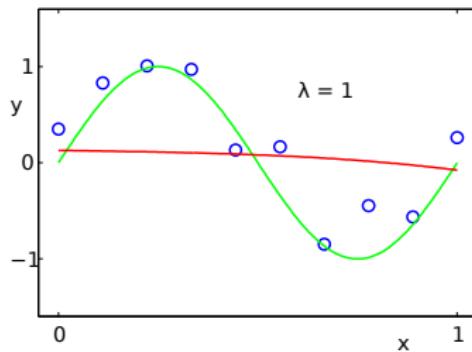
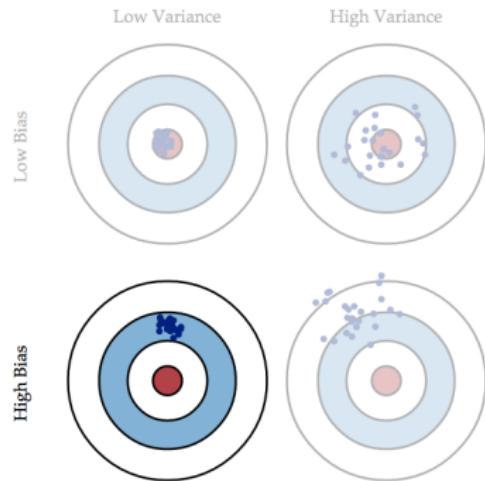
³See Bishop Section 3.2 for a more rigorous mathematical derivation

Bias-variance tradeoff: high bias

not flexibility (does not catch the data)

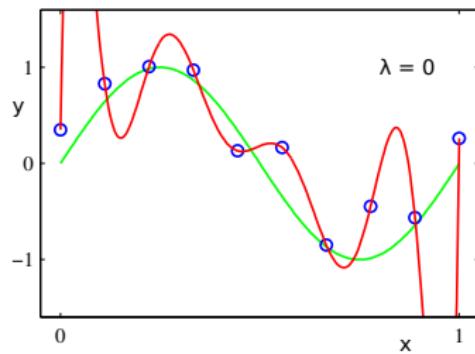
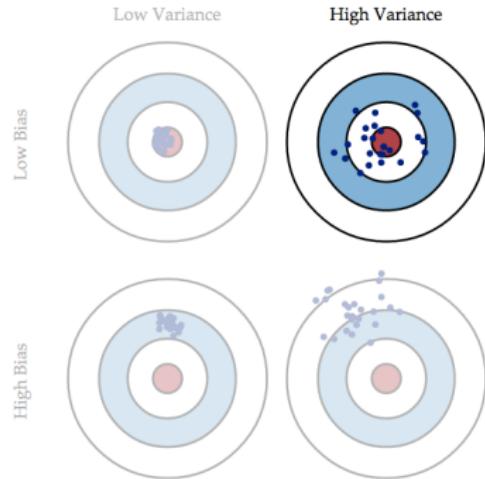
- In case of **high bias**, the model is too rigid to fit the underlying data distribution.
- This typically happens if the model is misspecified and/or the regularization strength λ is too high.

bad results



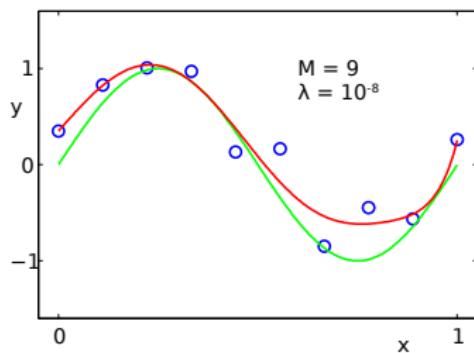
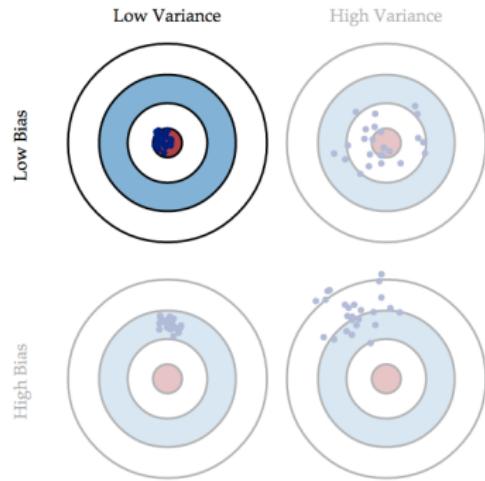
Bias-variance tradeoff: high variance

- In case of **high variance**, the model is too flexible, and therefore captures noise in the data.
- This is exactly what we call **overfitting**.
- This typically happens when the model has high capacity (= it "memorizes" the training data) and/or λ is too low.



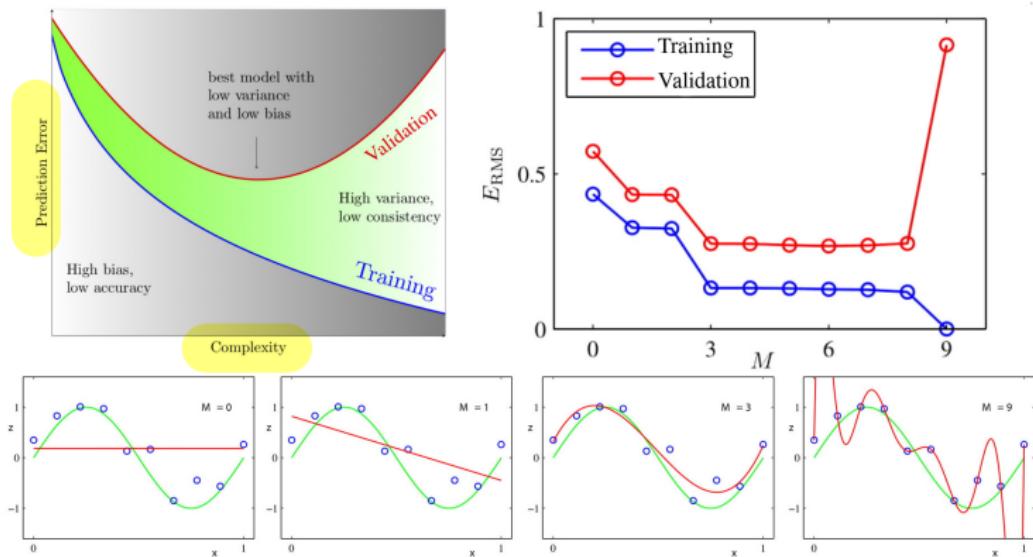
Bias-variance tradeoff

- Of course, we want models that have low bias and low variance, but often those are conflicting goals.
- A popular technique is to select a model with large capacity (e.g. high degree polynomial), and keep the variance in check by choosing appropriate regularization strength λ .



Bias-variance tradeoff

- Bias-variance tradeoff in the case of unregularized least squares regression ($\lambda = 0$)



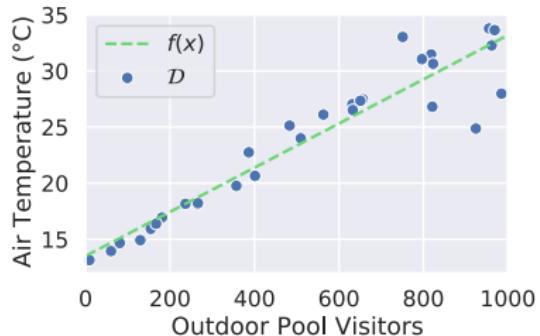
The upper-left figure from: <https://eisanematollahi.com/wp-content/uploads/2018/09/Machine-Learning-Basics-1.pdf>.

Correlation vs. Causation

Least squares fit

$$f(x) = 0.018x + 13.43$$

prediction



- The weights w_i can be interpreted as the strength of the (linear) relationship between feature x_i and y
- A weight of 0.018 shows a strong correlation (considering the different scales)
 - With actual data, you would normalize the data to handle the different scales of X and y and find a weight of about 1
- But correlation does not imply causation! Putting more people in the pool does not increase the air temperature.

Section 2

Probabilistic Linear Regression

In the following section, we will use probabilistic graphical models. If you do not know them yet, watch our separate Introduction to PGMs video.

Probabilistic formulation of linear regression

Remember from our problem definition at the start of the lecture,

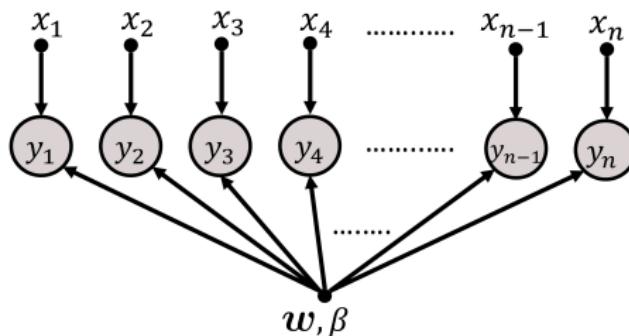
$$y_i = f_{\mathbf{w}}(\mathbf{x}_i) + \underbrace{\epsilon_i}_{\text{noise}}$$

Noise has zero-mean Gaussian distribution with a fixed precision $\beta = \frac{1}{\sigma^2}$

$$\epsilon_i \sim \mathcal{N}(0, \beta^{-1})$$

This implies that the distribution of the targets is

$$y_i \sim \mathcal{N}(f_{\mathbf{w}}(\mathbf{x}_i), \beta^{-1})$$



Remember: any function can be represented as $f_{\mathbf{w}}(\mathbf{x}_i) = \mathbf{w}^T \phi(\mathbf{x}_i)$

Maximum likelihood

Likelihood of a single sample

$$p(y_i \mid f_{\mathbf{w}}(\mathbf{x}_i), \beta) = \mathcal{N}(y_i \mid f_{\mathbf{w}}(\mathbf{x}_i), \beta^{-1}) \quad (25)$$

Assume that the samples are drawn independently
⇒ likelihood of the entire dataset $\mathcal{D} = \{\mathbf{X}, \mathbf{y}\}$ is

$$p(\mathbf{y} \mid \mathbf{X}, \mathbf{w}, \beta) = \prod_{i=1}^N p(y_i \mid f_{\mathbf{w}}(\mathbf{x}_i), \beta) \quad (26)$$

We can now use the same approach we used in previous lecture -
maximize the likelihood w.r.t. \mathbf{w} and β

$$\mathbf{w}_{\text{ML}}, \beta_{\text{ML}} = \arg \max_{\mathbf{w}, \beta} p(\mathbf{y} \mid \mathbf{X}, \mathbf{w}, \beta) \quad (27)$$

Maximum likelihood

Like in the coin flip example, we can make a few simplifications

$$\boldsymbol{w}_{\text{ML}}, \beta_{\text{ML}} = \arg \max_{\boldsymbol{w}, \beta} p(\boldsymbol{y} \mid \boldsymbol{X}, \boldsymbol{w}, \beta) \quad (28)$$

$$= \arg \max_{\boldsymbol{w}, \beta} \ln p(\boldsymbol{y} \mid \boldsymbol{X}, \boldsymbol{w}, \beta) \quad (29)$$

$$= \arg \min_{\boldsymbol{w}, \beta} -\ln p(\boldsymbol{y} \mid \boldsymbol{X}, \boldsymbol{w}, \beta) \quad (30)$$

Let's denote this quantity as **maximum likelihood error function** that we need to minimize

$$E_{\text{ML}}(\boldsymbol{w}, \beta) = -\ln p(\boldsymbol{y} \mid \boldsymbol{X}, \boldsymbol{w}, \beta) \quad (31)$$

Maximum likelihood

Simplify the error function

$$E_{\text{ML}}(\mathbf{w}, \beta) = -\ln \left[\prod_{i=1}^N \mathcal{N}(y_i | f_{\mathbf{w}}(\mathbf{x}_i), \beta^{-1}) \right] \quad (32)$$

$$= -\ln \left[\prod_{i=1}^N \sqrt{\frac{\beta}{2\pi}} \exp \left(-\frac{\beta}{2} (\mathbf{w}^T \phi(\mathbf{x}_i) - y_i)^2 \right) \right] \quad (33)$$

$$= -\sum_{i=1}^N \ln \left[\sqrt{\frac{\beta}{2\pi}} \exp \left(-\frac{\beta}{2} (\mathbf{w}^T \phi(\mathbf{x}_i) - y_i)^2 \right) \right] \quad (34)$$

$$= \frac{\beta}{2} \sum_{i=1}^N (\mathbf{w}^T \phi(\mathbf{x}_i) - y_i)^2 - \frac{N}{2} \ln \beta + \frac{N}{2} \ln 2\pi \quad (35)$$

Optimizing log-likelihood w.r.t. \mathbf{w}

$$\mathbf{w}_{\text{ML}} = \arg \min_{\mathbf{w}} E_{\text{ML}}(\mathbf{w}, \beta) \quad (36)$$

$$= \arg \min_{\mathbf{w}} \left[\frac{\beta}{2} \sum_{i=1}^N (\mathbf{w}^T \phi(\mathbf{x}_i) - y_i)^2 - \underbrace{\frac{N}{2} \ln \beta + \frac{N}{2} \ln 2\pi}_{= \text{const}} \right] \quad (37)$$

$$= \arg \min_{\mathbf{w}} \frac{1}{2} \sum_{i=1}^N (\mathbf{w}^T \phi(\mathbf{x}_i) - y_i)^2 \quad (38)$$

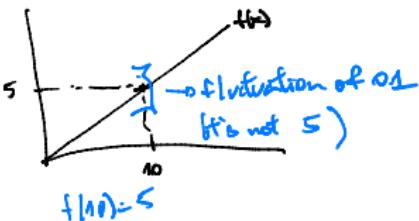
least squares error fn!

$$= \arg \min_{\mathbf{w}} E_{\text{LS}}(\mathbf{w}) \quad (39)$$

Maximizing the likelihood is equivalent to minimizing the least squares error function!

$$\mathbf{w}_{\text{ML}} = (\Phi^T \Phi)^{-1} \Phi^T \mathbf{y} = \Phi^\dagger \mathbf{y} \quad (40)$$

Optimizing log-likelihood w.r.t. β



Plug in the estimate for w and minimize w.r.t. β

$$\beta_{\text{ML}} = \arg \min_{\beta} E_{\text{ML}}(\mathbf{w}_{\text{ML}}, \beta)$$

$$N(f(\beta), \sigma^2) \quad (41)$$

$$= \arg \min_{\beta} \left[\frac{\beta}{2} \sum_{i=1}^N (\mathbf{w}_{\text{ML}}^T \phi(\mathbf{x}_i) - y_i)^2 - \frac{N}{2} \ln \beta + \frac{N}{2} \ln 2\pi \right] \quad (42)$$

Take derivative w.r.t. β and set it to zero

$$\frac{\partial}{\partial \beta} E_{\text{ML}}(\mathbf{w}_{\text{ML}}, \beta) = \frac{1}{2} \sum_{i=1}^N (\mathbf{w}_{\text{ML}}^T \phi(\mathbf{x}_i) - y_i)^2 - \frac{N}{2\beta} \stackrel{!}{=} 0 \quad (43)$$

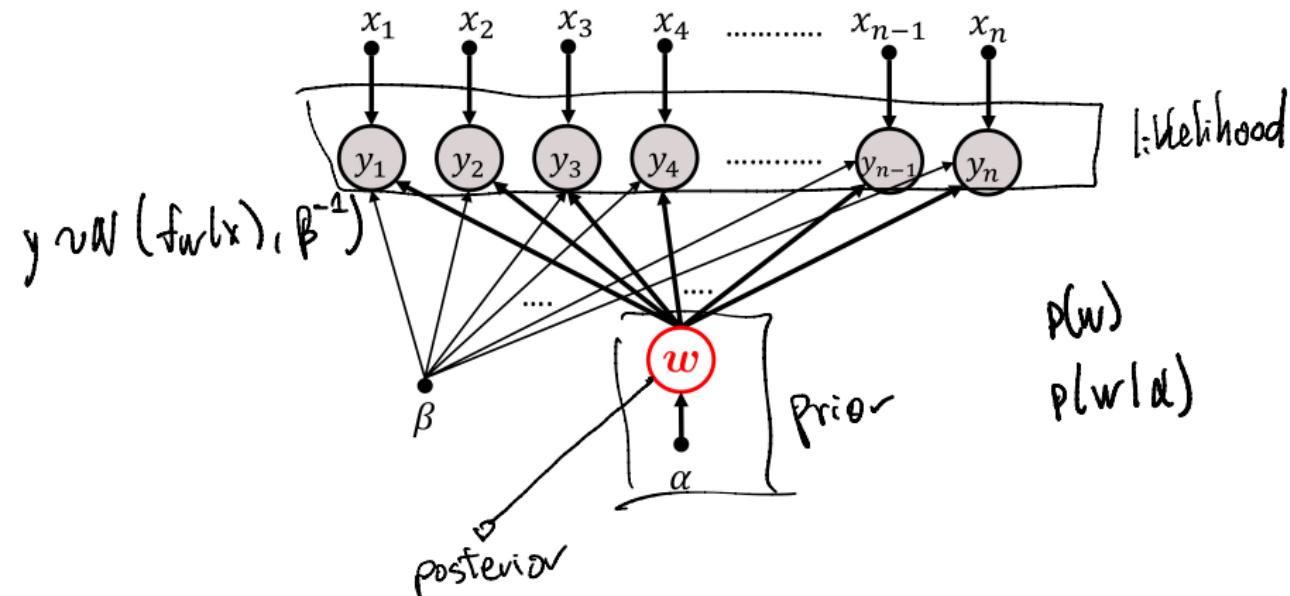
Solving for β

$$\frac{1}{\beta_{\text{ML}}} = \frac{1}{N} \sum_{i=1}^N (\mathbf{w}_{\text{ML}}^T \phi(\mathbf{x}_i) - y_i)^2 \quad (44)$$

Posterior distribution

Recall from the Lecture 3, that the MLE leads to overfitting (especially, when little training data is available).

Solution - consider the **posterior distribution** instead



Posterior distribution

Recall from the Lecture 3, that the MLE leads to overfitting (especially, when little training data is available).

Solution - consider the **posterior distribution** instead

$$p(\mathbf{w} \mid \mathbf{X}, \mathbf{y}, \beta, \cdot) = \frac{\underbrace{p(\mathbf{y} \mid \mathbf{X}, \mathbf{w}, \beta)}_{\text{likelihood}} \cdot \underbrace{p(\mathbf{w} \mid \cdot)}_{\text{prior}}}{\underbrace{p(\mathbf{y} \mid \mathbf{X}, \beta, \cdot)}_{\text{normalizing constant}}} \quad (45)$$

$$\propto p(\mathbf{y} \mid \mathbf{X}, \mathbf{w}, \beta) \cdot p(\mathbf{w} \mid \cdot) \quad (46)$$

Connection to the coin flip example

	train data	likelihood	prior	posterior
coin:	$\mathcal{D} = \mathbf{X}$	$p(\mathcal{D} \mid \theta)$	$p(\theta \mid a, b)$	$p(\theta \mid \mathcal{D})$
regr.:	$\mathcal{D} = \{\mathbf{X}, \mathbf{y}\}$	$p(\mathbf{y} \mid \mathbf{X}, \mathbf{w}, \beta)$	$p(\mathbf{w} \mid \cdot)$	$p(\mathbf{w} \mid \mathbf{X}, \mathbf{y}, \beta, \cdot)$

How do we choose the prior $p(\mathbf{w} \mid \cdot)$?

Precision $\beta = 1/\sigma^2$ is treated as a known parameter to simplify the calculations.

Prior for w

We set the prior over w to an isotropic multivariate normal distribution with zero mean

$$p(w | \alpha) = \mathcal{N}(w | \mathbf{0}, \alpha^{-1} \mathbf{I}) = \left(\frac{\alpha}{2\pi} \right)^{\frac{M}{2}} \exp \left(-\frac{\alpha}{2} w^T w \right) \quad (47)$$

where,

α - precision of the distribution

M - number of elements in the vector w

Motivation:

- Higher probability is assigned to small values of $w \implies$ prevents overfitting (recall slide 20)
- Likelihood is also Gaussian - simplified calculations

Maximum a posteriori (MAP)

We are looking for \mathbf{w} that corresponds to the mode of the posterior

$$\mathbf{w}_{\text{MAP}} = \arg \max_{\mathbf{w}} p(\mathbf{w} | \mathbf{X}, \mathbf{y}, \alpha, \beta) \quad (48)$$

$$= \arg \max_{\mathbf{w}} \underbrace{\ln p(\mathbf{y} | \mathbf{X}, \mathbf{w}, \beta)}_{\text{likelihood}} + \underbrace{\ln p(\mathbf{w} | \alpha)}_{\text{prior}} - \underbrace{\ln p(\mathbf{y} | \mathbf{X}, \beta, \alpha)}_{\text{evidence} = \text{const}} \quad (49)$$

posterior

$$= \arg \min_{\mathbf{w}} -\ln p(\mathbf{y} | \mathbf{X}, \mathbf{w}, \beta) - \ln p(\mathbf{w} | \alpha) \quad (50)$$

Similar to ML, define the MAP error function as negative log-posterior

$$E_{\text{MAP}}(\mathbf{w}) = -\ln p(\mathbf{w} | \mathbf{X}, \mathbf{y}, \alpha, \beta) \quad (51)$$

$$= -\ln p(\mathbf{y} | \mathbf{X}, \mathbf{w}, \beta) - \ln p(\mathbf{w} | \alpha) + \text{const} \quad (52)$$

We ignore the constant terms in the error function, as they are independent of \mathbf{w}

MAP error function

Simplify the error function

$$\begin{aligned} E_{MAP} &= -\ln p(\mathbf{y} \mid \mathbf{X}, \mathbf{w}, \beta) - \ln p(\mathbf{w} \mid \alpha) \\ &= \frac{\beta}{2} \sum_{i=1}^N (\mathbf{w}^T \phi(\mathbf{x}_i) - y_i)^2 - \frac{N}{2} \ln \beta + \frac{N}{2} \ln 2\pi \quad \left. \begin{array}{l} \text{lklhood} \\ \text{prior} \end{array} \right\} \\ &\quad - \frac{M}{2} \ln \left(\frac{\alpha}{2\pi} \right) + \frac{\alpha}{2} \mathbf{w}^T \mathbf{w} \\ &= \frac{\beta}{2} \sum_{i=1}^N (\mathbf{w}^T \phi(\mathbf{x}_i) - y_i)^2 + \frac{\alpha}{2} \|\mathbf{w}\|_2^2 + \text{const} \\ &\propto \frac{1}{2} \sum_{i=1}^N (\mathbf{w}^T \phi(\mathbf{x}_i) - y_i)^2 + \frac{\lambda}{2} \|\mathbf{w}\|_2^2 + \text{const} \quad \text{where } \lambda = \frac{\alpha}{\beta} \\ &\qquad \qquad \qquad \boxed{\text{ridge regression error fn!}} \\ &\qquad \qquad \qquad \propto E_{\text{ridge}}(\mathbf{w}) + \text{const} \end{aligned} \tag{53}$$

MAP estimation with Gaussian prior is equivalent to ridge regression!

Full Bayesian approach

Instead of representing $p(\mathbf{w} | \mathcal{D})$ with the point estimate \mathbf{w}_{MAP} , we can compute the full posterior distribution

$$p(\mathbf{w} | \mathcal{D}) \propto p(\mathbf{y} | \mathbf{X}, \mathbf{w}, \beta) p(\mathbf{w} | \alpha). \quad (54)$$

Since both likelihood and prior are Gaussian, the posterior is as well!⁴

$$p(\mathbf{w} | \mathcal{D}) = \mathcal{N}(\mathbf{w} | \boldsymbol{\mu}, \boldsymbol{\Sigma})$$

where $\boldsymbol{\mu} = \beta \boldsymbol{\Sigma} \boldsymbol{\Phi}^T \mathbf{y}$ and $\boldsymbol{\Sigma}^{-1} = \alpha \mathbf{I} + \beta \boldsymbol{\Phi}^T \boldsymbol{\Phi}$.

Observations

- The posterior is Gaussian, so its mode is the mean and $\mathbf{w}_{\text{MAP}} = \boldsymbol{\mu}$
- In the limit of an infinitely broad prior $\alpha \rightarrow 0$, $\mathbf{w}_{\text{MAP}} \rightarrow \mathbf{w}_{\text{ML}}$
- For $N = 0$, i.e. no data points, the posterior equals the prior
- Even though we assume an isotropic prior $p(\mathbf{w})$, the posterior covariance is in general not diagonal

⁴The Gaussian distribution is a *conjugate prior* of itself

Predicting for new data: MLE and MAP

After observing data $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^N$, we can compute the MLE/MAP.

Usually, what we are actually interested in is the prediction \hat{y}_{new} for a new data point x_{new} - the model parameters w are just a means to achieve this.

Recall, that $y \sim \mathcal{N}(f_w(x), \beta^{-1})$

Plugging in the estimated parameters we get a predictive distribution that lets us make prediction \hat{y}_{new} for new data x_{new} .

- Maximum likelihood: w_{ML} and β_{ML}

$$p(\hat{y}_{new} | x_{new}, w_{ML}, \beta_{ML}) = \mathcal{N}(\hat{y}_{new} | w_{ML}^T \phi(x_{new}), \beta_{ML}^{-1}) \quad (55)$$

- Maximum a posteriori: w_{MAP}

↑ reaching the same

$$p(\hat{y}_{new} | x_{new}, w_{MAP}, \beta) = \mathcal{N}(\hat{y}_{new} | w_{MAP}^T \phi(x_{new}), \beta^{-1}) \quad (56)$$

Recall, that we assume β to be known a priori (for simplified calculations).

Posterior predictive distribution

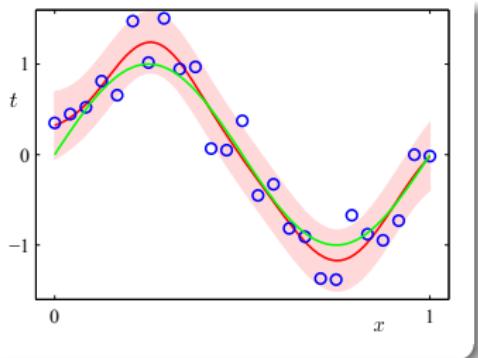
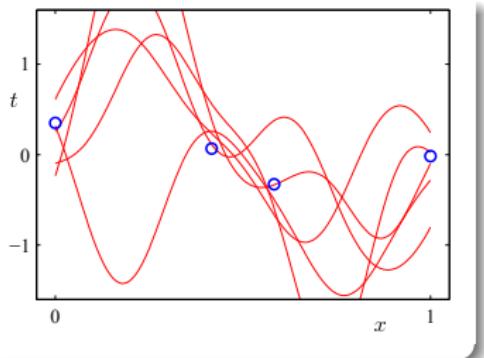
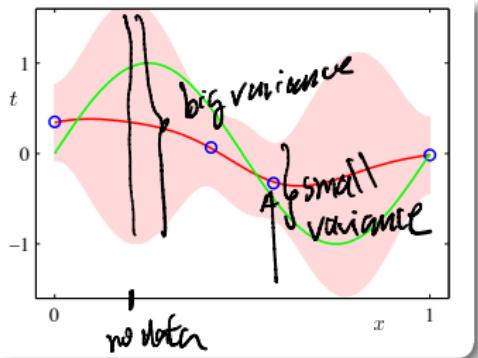
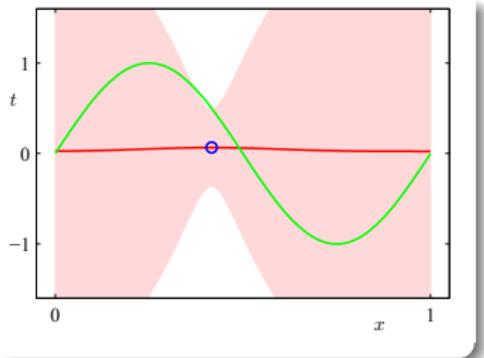
Alternatively, we can use the full posterior distribution $p(\mathbf{w} | \mathcal{D})$.

This allows us to compute the **posterior predictive distribution**

$$\begin{aligned} p(\hat{y}_{new} | \mathbf{x}_{new}, \mathcal{D}) &= \int p(\hat{y}_{new}, \mathbf{w} | \mathbf{x}_{new}, \mathcal{D}) d\mathbf{w} \\ &= \int p(\hat{y}_{new} | \mathbf{x}_{new}, \mathbf{w}) p(\mathbf{w} | \mathcal{D}) d\mathbf{w} \quad \text{the variable may change} \\ &= \mathcal{N}(\hat{y}_{new} | \boldsymbol{\mu}^T \phi(\mathbf{x}_{new}), \beta^{-1} + \phi(\mathbf{x}_{new})^T \boldsymbol{\Sigma} \phi(\mathbf{x}_{new})) \end{aligned}$$

Advantage: We get a more accurate estimate about the uncertainty in the prediction (i.e. the variance of the Gaussian, which now also depends on the input \mathbf{x}_{new})

Example of posterior predictive distribution



Green: Underlying function, Blue: Observations, Dark-Red: Mode, Light-Red: Variance

Summary

- Optimization-based approaches to regression have probabilistic interpretations
 - Least squares regression \iff Maximum likelihood (Slide 32)
 - Ridge regression \iff Maximum a posteriori (Slide 38)
- Even nonlinear dependencies in the data can be captured by a model linear w.r.t. weights w (Slide 13)
- Penalizing large weights helps to reduce overfitting (Slide 20)
- Full Bayesian gives us data-dependent uncertainty estimates (Slide 41)

Reading material

Main reading

- “Pattern Recognition and Machine Learning” by Bishop
[ch. 1.1, 3.1, 3.2, 3.3.1, 3.3.2, 3.6]

Extra reading

- “Machine Learning: A Probabilistic Perspective” by Murphy
[ch. 7.2–7.3, 7.5.1, 7.6.1, 7.6.2]

Slides are based on an older version by G. Jensen and C. Osendorfer. Some figures are from Bishop's “Pattern Recognition and Machine Learning”.