

Machine Learning and Data Mining

Recapitulation

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Fundamentals of statistics

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Two schools of statistics

Frequentist statistics:

- probability = long-run frequency of events;
- parameters are fixed but unknown constants;
- inference based on sampling distributions;
- methods: MLE, hypothesis testing, confidence intervals.

Bayesian statistics:

- probability = degree of belief;
- parameters are random variables with distributions;
- inference via Bayes' theorem: $P(\theta | X) \propto P(X | \theta)P(\theta)$;
- methods: posterior distributions, credible intervals, MAP.

Random variables

Random variable:

- a measurable function $X : \Omega \rightarrow \mathbb{R}$;
- maps outcomes from sample space to real numbers.

Types:

- **discrete:** $X \in \{x_1, x_2, \dots\}$;
 - probability mass function: $P(X = x)$;
 - examples: coin flip, die roll, number of defects;
- **continuous:** $X \in \mathbb{R}$;
 - probability density function: $p(x)$;
 - examples: height, temperature, measurement error.

Random variables: discrete examples

Discrete examples:

- coin flip: $X \in \{0, 1\}$, $P(X = 1) = p$;
- die roll: $X \in \{1, 2, 3, 4, 5, 6\}$, $P(X = k) = 1/6$;
- number of customers per hour: $X \in \{0, 1, 2, \dots\}$.

Properties:

- finite or countably infinite outcomes;
- $\sum_x P(X = x) = 1$.

Random variables: continuous examples

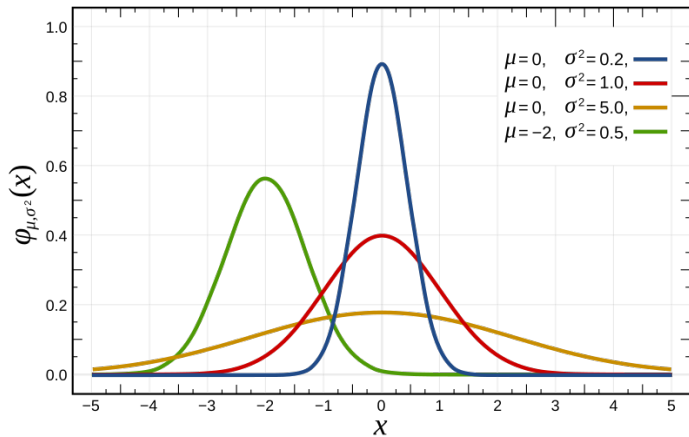
Normal distribution: $X \sim \mathcal{N}(\mu, \sigma^2)$

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

Examples:

- person's height: $X \sim \mathcal{N}(170, 10^2)$ cm;
- measurement error: $X \sim \mathcal{N}(0, \sigma^2)$.

Normal distribution: visualization



Source: commons.wikimedia.org

Multivariate normal distribution

Multivariate normal: $\mathbf{X} \sim \mathcal{N}(\boldsymbol{\mu}, \Sigma)$

$$p(\mathbf{x}) = \frac{1}{(2\pi)^{d/2} |\Sigma|^{1/2}} \exp \left[-\frac{1}{2} (\mathbf{x} - \boldsymbol{\mu})^T \Sigma^{-1} (\mathbf{x} - \boldsymbol{\mu}) \right]$$

where:

- $\mathbf{x} \in \mathbb{R}^d$ — random vector;
- $\boldsymbol{\mu} \in \mathbb{R}^d$ — mean vector: $\mu_i = \mathbb{E}[X_i]$;
- $\Sigma \in \mathbb{R}^{d \times d}$ — covariance matrix: $\Sigma_{ij} = \text{Cov}[X_i, X_j]$;
- $|\Sigma|$ — determinant of Σ .

Multivariate normal: covariance matrix

Covariance matrix Σ :

$$\Sigma_{ij} = \text{Cov}[X_i, X_j] = \mathbb{E}[(X_i - \mu_i)(X_j - \mu_j)]$$

Properties:

- symmetric: $\Sigma = \Sigma^T$;
- positive semi-definite: $\mathbf{v}^T \Sigma \mathbf{v} \geq 0$ for all \mathbf{v} ;
- diagonal elements: $\Sigma_{ii} = \mathbb{D}[X_i]$;
- off-diagonal: correlation between variables.

Multivariate normal: special cases

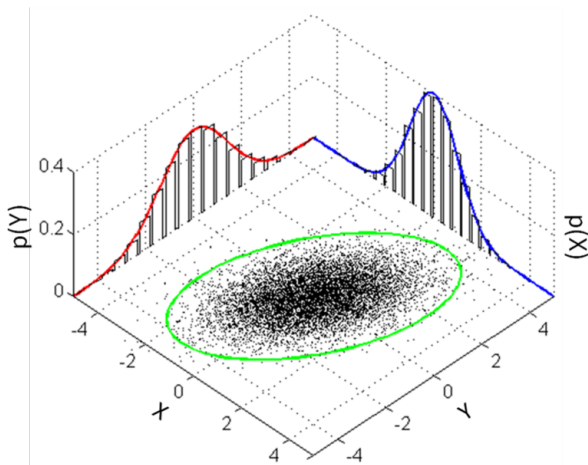
Independent components: $\Sigma = \text{diag}(\sigma_1^2, \dots, \sigma_d^2)$

$$p(\mathbf{x}) = \prod_{i=1}^d \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp \left[-\frac{(x_i - \mu_i)^2}{2\sigma_i^2} \right]$$

Spherical (isotropic): $\Sigma = \sigma^2 I$

$$p(\mathbf{x}) = \frac{1}{(2\pi\sigma^2)^{d/2}} \exp \left[-\frac{\|\mathbf{x} - \boldsymbol{\mu}\|^2}{2\sigma^2} \right]$$

Multivariate normal: visualization



3D surface and contour plots of bivariate normal distribution.

Source: commons.wikimedia.org

Random variables: expectation

Expectation (mean):

$$\mathbb{E}[X] = \begin{cases} \sum_x x \cdot P(X = x) & \text{discrete} \\ \int x \cdot p(x) \, dx & \text{continuous} \end{cases}$$

Variance:

$$\begin{aligned} \mathbb{D}[X] &= \mathbb{E}[(X - \mathbb{E}[X])^2] \\ &= \mathbb{E}[X^2] - (\mathbb{E}[X])^2 \end{aligned}$$

Statistical estimators

Given:

- sample: $X = \{x_1, \dots, x_n\}$ from distribution $P(x \mid \theta)$;
- unknown parameter: θ .

Estimator: $\hat{\theta}(X)$ — a function of sample.

Examples:

- sample mean: $\hat{\mu} = \frac{1}{n} \sum_{i=1}^n x_i$;
- sample variance: $\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \hat{\mu})^2$.

Bias of an estimator

Bias:

$$\text{Bias}[\hat{\theta}] = \mathbb{E}[\hat{\theta}] - \theta$$

Unbiased estimator:

$$\mathbb{E}[\hat{\theta}] = \theta \quad \Leftrightarrow \quad \text{Bias}[\hat{\theta}] = 0$$

Asymptotically unbiased estimator

Asymptotically unbiased:

$$\lim_{n \rightarrow \infty} \mathbb{E}[\hat{\theta}_n] = \theta$$

or equivalently:

$$\lim_{n \rightarrow \infty} \text{Bias}[\hat{\theta}_n] = 0$$

- bias vanishes as sample size grows;
- weaker condition than unbiasedness.

Examples: biased vs unbiased

Sample mean for μ :

$$\hat{\mu} = \frac{1}{n} \sum_{i=1}^n x_i$$

- $\mathbb{E}[\hat{\mu}] = \mu$ — **unbiased**.

Sample variance for σ^2 :

$$\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \hat{\mu})^2$$

- $\mathbb{E}[\hat{\sigma}^2] = \frac{n-1}{n} \sigma^2$ — **biased**;
- asymptotically unbiased: $\lim_{n \rightarrow \infty} \mathbb{E}[\hat{\sigma}^2] = \sigma^2$.

Unbiased sample variance

Unbiased estimator for σ^2 :

$$s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \hat{\mu})^2$$

then:

$$\mathbb{E}[s^2] = \sigma^2$$

- division by $n - 1$ (Bessel's correction) accounts for using estimated mean;
- loses one degree of freedom.

Example: asymptotically unbiased wins

Compare variance estimators (assuming $X_i \sim \mathcal{N}(\mu, \sigma^2)$):

Unbiased: $s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2$

- $\mathbb{E}[s^2] = \sigma^2$;
- $\mathbb{D}[s^2] = \frac{2\sigma^4}{n-1}$.

MLE (biased): $\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2$

- $\mathbb{E}[\hat{\sigma}^2] = \frac{n-1}{n} \sigma^2$ — biased;
- $\mathbb{D}[\hat{\sigma}^2] = \frac{2(n-1)\sigma^4}{n^2} < \mathbb{D}[s^2]$ — **lower variance!**

Example: asymptotically unbiased wins

Comparison:

$$\frac{\mathbb{D}[\hat{\sigma}^2]}{\mathbb{D}[s^2]} = \frac{(n-1)^2}{n^2} \approx 1 - \frac{2}{n}$$

- MLE has $\frac{2}{n}$ less variance;
- bias: $\text{Bias}[\hat{\sigma}^2] = -\frac{\sigma^2}{n} \rightarrow 0$;
- for large n : MLE dominates in MSE;
- tradeoff: small bias buys significant variance reduction.

Counter example: unbiased but bad

Estimator using only first element:

$$\hat{\mu}_1 = x_1$$

For estimating $\mu = \mathbb{E}[X_i]$:

- $\mathbb{E}[\hat{\mu}_1] = \mathbb{E}[x_1] = \mu$ — **unbiased**;
- $\mathbb{D}[\hat{\mu}_1] = \sigma^2$ — does **not** decrease with n ;
- **not consistent**: does not converge to μ ;
- wasteful: ignores $n - 1$ observations.

Counter example: comparison

Compare $\hat{\mu}_1 = x_1$ vs $\hat{\mu} = \frac{1}{n} \sum_{i=1}^n x_i$:

Property	$\hat{\mu}_1$	$\hat{\mu}$
Unbiased	✓	✓
Variance	σ^2	σ^2/n
Consistent	×	✓
MSE	σ^2	σ^2/n

Lesson: unbiasedness alone is not sufficient for a good estimator.

Mean Squared Error

Mean Squared Error:

$$\begin{aligned}\text{MSE}[\hat{\theta}] &= \mathbb{E}[(\hat{\theta} - \theta)^2] \\ &= \text{Bias}[\hat{\theta}]^2 + \mathbb{D}[\hat{\theta}]\end{aligned}$$

Bias-variance decomposition:

- unbiased estimator may have high variance;
- slightly biased estimator may have lower MSE;
- fundamental tradeoff in machine learning.

Example: biased but better MSE

Estimating variance with shrinkage:

Given $X_1, \dots, X_n \sim \mathcal{N}(\mu, \sigma^2)$, consider:

- unbiased: $s^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2$;
- biased: $\hat{\sigma}_c^2 = \frac{1}{n+1} \sum_{i=1}^n (x_i - \bar{x})^2$.

For small n , $\text{MSE}[\hat{\sigma}_c^2] < \text{MSE}[s^2]$!

Tradeoff: accepting bias reduces variance enough to lower MSE.

Consistent estimator:

$$\hat{\theta}_n \xrightarrow{P} \theta \quad \text{as } n \rightarrow \infty$$

i.e., $\forall \varepsilon > 0$:

$$\lim_{n \rightarrow \infty} P(|\hat{\theta}_n - \theta| > \varepsilon) = 0$$

- converges in probability to true parameter;
- weaker than unbiasedness (concerns large n behavior).

Example: inconsistent estimator

Constant estimator:

$$\hat{\mu}_0 = c \quad (\text{constant, independent of data})$$

For estimating $\mu = \mathbb{E}[X_i]$:

- $\mathbb{E}[\hat{\mu}_0] = c$ — biased (unless $c = \mu$ by chance);
- $\mathbb{D}[\hat{\mu}_0] = 0$ — zero variance!
- **not consistent:** $\hat{\mu}_0 \not\rightarrow \mu$ as $n \rightarrow \infty$;
- does not use data at all.

Another example: we already saw $\hat{\mu}_1 = x_1$ is unbiased but inconsistent.

Example: asymptotically unbiased but inconsistent

Estimator with noise:

$$\hat{\mu}_{\varepsilon} = \frac{1}{2} \left[\frac{1}{N} \sum_{i=1}^N x_i + x_1 \right]. \quad (1)$$

Properties:

- $\mathbb{E}[\hat{\mu}_{\varepsilon}] = \mu$ — unbiased for all n ;
- $P(|\hat{\mu}_{\varepsilon} - \mu| > \varepsilon) \not\rightarrow 0$.

Example: consistent but biased

Shrinkage estimator:

$$\hat{\mu}_s = \frac{1}{N} \sum_{i=1}^N x_i + \frac{c}{n}$$

where $c \neq 0$ is a constant.

Properties:

- $\mathbb{E}[\hat{\mu}_s] = \mu + \frac{c}{n}$ — biased for all finite n ;
- $\text{Bias}[\hat{\mu}_s] = \frac{c}{n} \rightarrow 0$ — asymptotically unbiased;
- $\hat{\mu}_s \xrightarrow{P} \mu$ — **consistent!**
- shows: consistency unbiasedness for finite n .

Statistical estimations

Setup

Given:

- data: $X = \{x_i\}_{i=1}^N$;
- parameterized family of distributions $P(x \mid \theta)$.

Problem:

- estimate θ .

Maximum likelihood estimation

$$\begin{aligned}L(\theta) &= P(X | \theta); \\ \hat{\theta} &= \arg \max_{\theta} L(\theta).\end{aligned}$$

$$\mathcal{L}(\theta) = -\log \prod_i P(x_i | \theta) = -\sum_i \log P(x_i | \theta)$$

- consistent estimation: $\hat{\theta} \rightarrow \theta$ as $N \rightarrow \infty$;
- *might be biased*;
- equal to MAP estimation with uniform prior.

MLE: example

Given samples $\{x_i\}_{i=1}^N$ from a normal distribution estimate its mean.

$$\mu = \arg \min_{\mu} \mathcal{L}(X) =$$

$$\arg \min_{\mu} u - \sum_i \log \left(\frac{1}{Z} \exp \left[-\frac{(x_i - \mu)^2}{2\sigma^2} \right] \right) =$$

$$\arg \min_{\mu} \sum_i (x_i - \mu)^2 = \frac{1}{N} \sum_i x_i$$

Maximum Likelihood Estimator:

$$\hat{\theta}_{\text{MLE}} = \arg \max_{\theta} P(X \mid \theta)$$

Key properties (under regularity conditions):

1. **Consistency:** $\hat{\theta}_{\text{MLE}} \xrightarrow{P} \theta$ as $n \rightarrow \infty$;
2. **Asymptotic normality:** $\sqrt{n}(\hat{\theta}_{\text{MLE}} - \theta) \xrightarrow{d} \mathcal{N}(0, I(\theta)^{-1})$;
3. **Asymptotic efficiency:** achieves Cramér-Rao lower bound.

Properties of MLE: bias

MLE is generally biased:

- $\mathbb{E}[\hat{\theta}_{\text{MLE}}] \neq \theta$ for finite n ;
- **asymptotically unbiased:** $\lim_{n \rightarrow \infty} \mathbb{E}[\hat{\theta}_{\text{MLE}}] = \theta$;
- bias often decreases as $O(1/n)$.

Example: MLE for variance σ^2 in normal distribution:

$$\hat{\sigma}_{\text{MLE}}^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \hat{\mu})^2$$

is biased but asymptotically unbiased.

Properties of MLE: efficiency

Fisher Information:

$$I(\theta) = \mathbb{E} \left[\left(\frac{\partial \log P(X | \theta)}{\partial \theta} \right)^2 \right]$$

Cramér-Rao bound:

$$\mathbb{D}[\hat{\theta}] \geq \frac{1}{n \cdot I(\theta)}$$

Asymptotically efficient:

- MLE achieves this bound as $n \rightarrow \infty$;
- no other consistent estimator has lower asymptotic variance.

Properties of MLE: invariance

Functional invariance:

If $\hat{\theta}_{\text{MLE}}$ is MLE for θ , then for any function g :

$$\widehat{g(\theta)}_{\text{MLE}} = g(\hat{\theta}_{\text{MLE}})$$

Example:

- MLE for μ in $\mathcal{N}(\mu, \sigma^2)$: $\hat{\mu} = \bar{x}$;
- MLE for μ^2 : $\widehat{\mu^2} = \bar{x}^2$ (not $\overline{x^2}$).

$$P(\theta \mid X) = \frac{1}{Z} P(X \mid \theta) P(\theta);$$

- often, posterior distribution of predictions is of the main interest:

$$P(f(x) = y \mid X) = \int \mathbb{I}[f(x, \theta) = y] P(\theta \mid X) d\theta$$

- with a few exceptions posterior is intractable;
- often, approximate inference is utilized instead.

BI: example

Given samples $\{x_i\}_{i=1}^N$ from a normal distribution estimate mean under a normal prior.

$$P(\mu \mid X) = \frac{1}{Z} P(X \mid \mu) P(\mu) =$$
$$\frac{1}{Z} \exp \left[-\frac{\mu^2}{2c^2} \right] \cdot \prod \exp \left[-\frac{(x_i - \mu)^2}{2\sigma^2} \right]$$

$$\log P(\mu \mid X) = -Z - \frac{\mu^2}{2c^2} - \sum_i \frac{(x_i - \mu)^2}{2\sigma^2}$$

Maximum a posteriori estimation

$$\begin{aligned}\hat{\theta} &= \arg \max_{\theta} P(\theta \mid X) = \arg \max_{\theta} P(X \mid \theta) P(\theta) = \\ &\arg \min_{\theta} [-\log P(X \mid \theta) - \log P(\theta)] = \\ &\arg \min_{\theta} [\text{neg log likelihood} + \text{penalty}]\end{aligned}$$

$$\hat{\theta} = \arg \min_{\theta} \left[-\log P(\theta) - \sum_i \log P(x_i \mid \theta) \right]$$

- sometimes called **structural loss**:
 - i.e. includes 'structure' of the predictor into the loss.

MAP: example

Given samples $\{x_i\}_{i=1}^N$ from a normal distribution estimate mean under a normal prior.

$$\begin{aligned}\hat{\mu} &= \arg \max_{\mu} \log P(\mu \mid X) = \\ &\arg \max_{\mu} \left[-Z - \frac{\mu^2}{2\sigma^2} - \sum_i \frac{(x_i - \mu)^2}{2\sigma^2} \right] = \\ &\arg \min_{\mu} \left[\lambda \mu^2 + \sum_i (x_i - \mu)^2 \right] = \frac{1}{N + \lambda} \sum_i x_i\end{aligned}$$

Machine Learning

Structure of a Machine Learning problem

Given:

- description of the problem:
 - prior knowledge;
- data:
 - input space: \mathcal{X} ;
 - output space: \mathcal{Y} ;
- metric M .

Problem:

- find a learning algorithm: $A : \mathcal{D} \rightarrow (\mathcal{X} \rightarrow \mathcal{Y})$ such that:

$$M(A(\text{data})) \rightarrow \max$$

Differences from statistics

Machine Learning:

- distributions are often intractable;
- high-dimensionality/small sample sizes;
- **universal approximators**;
- solves direct problem.

Statistics:

- process modelling;
- low-dimensionality/large sample sizes;
- (approx.) prob. distributions;
- **exact inference**;
- infers process parameters.

Supervised learning

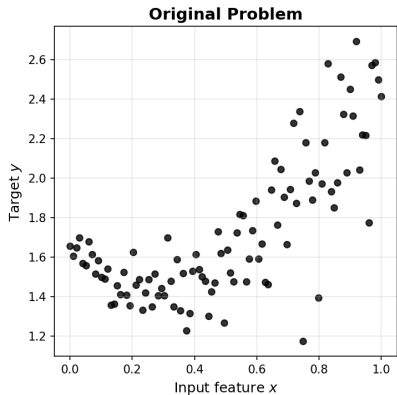
Regression

Input: $x \in \mathbb{R}^n$:

- samples;
- features;
- inputs;
- predictor (statistics).

Output: $y \in \mathbb{R}^m$:

- target;
- label;
- response.



(Ordinary) Regression

Given a sample from:

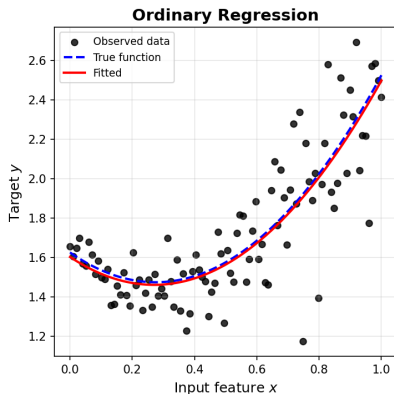
$$y = f(x) + \varepsilon;$$

$$\varepsilon \sim P(\varepsilon \mid x);$$

$$\mathbb{E}[\varepsilon \mid x] = 0.$$

find a model $m(x)$ such that:

$$m(x) \approx \mathbb{E}[y \mid x] f(x).$$



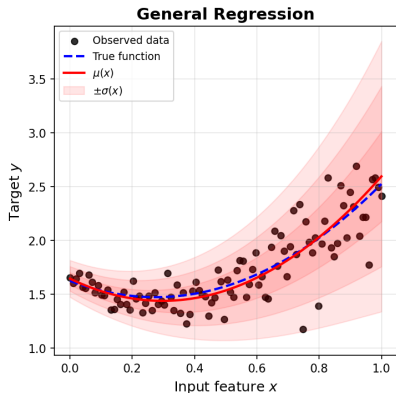
General Regression

Given a sample from:

$$y = P(y | x);$$

find a model $Q(y | x)$ such that:

$$Q(y | x) \approx P(y | x).$$



$$\begin{aligned}\mathcal{L}(f) &= - \sum_i \log P_y(y_i \mid f, x_i) = \\ &\quad - \sum_i \log P_\varepsilon(y_i - f(x_i) \mid f, x_i) = \\ &\quad - \sum_i \log P_\varepsilon(y_i - f(x_i) \mid x_i)\end{aligned}$$

Regression: MSE

- $\varepsilon \sim \mathcal{N}(0, \sigma_\varepsilon^2)$;
- $\sigma_\varepsilon^2 = \text{const}$ (unknown);

$$\begin{aligned}\mathcal{L}(f) &= - \sum_i \log P_\varepsilon(y_i - f(x_i) \mid x_i) = \\ &\sum_i \left[Z(\sigma_\varepsilon^2) - \frac{(y_i - f(x_i))^2}{2\sigma_\varepsilon^2} \right] \sim \\ &\sum_i (y_i - f(x_i))^2 \rightarrow \min\end{aligned}$$

$$f^*(x) = \mathbb{E}[y \mid x]$$

Regression: MAE

- $\varepsilon \sim \text{Laplace}(0, b_\varepsilon)$;
- $b_\varepsilon = \text{const}$ (unknown);

$$\begin{aligned}\mathcal{L}(f) &= - \sum_i \log P_\varepsilon(y_i - f(x_i) \mid x_i) = \\ &\sum_i \left[Z(b_\varepsilon) - \frac{|y_i - f(x_i)|}{2b_\varepsilon} \right] \sim \\ &\sum_i |y_i - f(x_i)| \rightarrow \min\end{aligned}$$

$$f^*(x) = \text{median}[y \mid x]$$

Linear regression

$$f(x) = w \cdot x$$

$$\mathcal{L}(w) = \sum_i (w \cdot x_i - y_i)^2 = \|Xw - y\|^2 \rightarrow \min;$$

$$\frac{\partial}{\partial w} \mathcal{L}(w) = 2X^T(Xw - y) = 0;$$

$$w = (X^T X)^{-1} X^T y.$$

$$\begin{aligned}\mathcal{L}(w) &= \sum_i (w \cdot x_i - y_i)^2 + \lambda \|w\|^2 = \\ &\quad \|Xw - y\|^2 + \lambda \|w\|^2 \rightarrow \min; \\ \frac{\partial}{\partial w} \mathcal{L}(w) &= 2X^T(Xw - y) + 2\lambda w = 0; \\ w &= (X^T X + \lambda I)^{-1} X^T y.\end{aligned}$$

Linear regression + MSE + Bayesian Inference

- prior:

$$w \sim \mathcal{N}(0, \Sigma_w);$$

- data model:

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

Linear regression + MSE + Bayesian Inference

$$P(w \mid y, X) \propto P(y \mid w, X)P(w) \propto$$

$$\exp \left[-\frac{1}{2\sigma_\varepsilon^2} (y - Xw)^T (y - Xw) \right] \cdot \exp \left[-\frac{1}{2} w^T \Sigma_w^{-1} w \right] =$$

$$\exp \left[-\frac{1}{2} (w - w^*)^T A_w (w - w^*) \right]$$

where:

- $A_w = \frac{1}{\sigma_\varepsilon^2} XX^T + \Sigma_w^{-1};$
- $w^* = \frac{1}{\sigma_\varepsilon^2} A_w^{-1} Xy.$

To make prediction y' in point x' :

$$\begin{aligned} P(y' \mid y, X, x') = \\ \int P(y' \mid w, x') P(w \mid X, y) = \\ \mathcal{N} \left(\frac{1}{\sigma_{\varepsilon}^2} x'^T A^{-1} X y, x'^T A^{-1} x' \right) \end{aligned}$$

Basis expansion

To capture more complex dependencies basis functions can be introduced:

$$f(x) = \sum_i w \cdot \phi(x)$$

where:

- $\phi(x) \in \mathbb{R}^K$ — expanded basis.
- ϕ is fixed.

Basis expansion: example

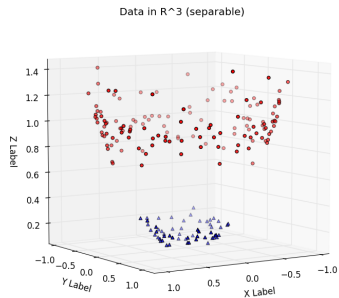
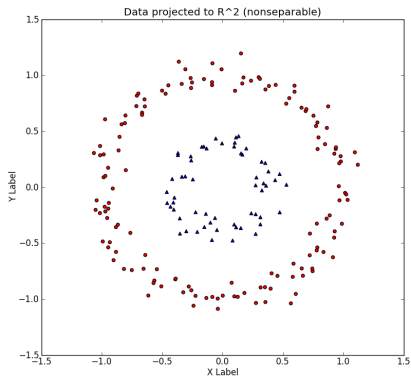
Regression with polynomials:

$$\phi(x) = \{1, x_1, \dots, x_n, x_1^2, x_1x_2, \dots, x_n^2, \dots\}$$

Periodic functions:

$$\phi(x) = \{1, \sin(x), \cos(x), \sin(2x), \cos(2x), \dots\}$$

Basis expansion: example



Source: eric-kim.net

Classification

- classes: $y \in \{1, 2, \dots, m\}$;
- classifier:

$$f: \mathcal{X} \rightarrow \mathbb{R}^m;$$
$$\sum_{k=1}^m f^k(x) = 1.$$

$$\mathcal{L}(f) = - \sum_i \sum_{k=1}^m \mathbb{I}[y_i = k] \log f^k(x_i);$$
$$\text{cross-entropy}(f) = \sum_i y'_i \cdot f(x_i).$$

- often employed trick to make $f(x)$ a proper distribution:

$$f(x) = \text{softmax}(g(x));$$

$$f^i(x) = \frac{\exp(g^i(x))}{\sum_k \exp(g^k(x))}.$$

$$\begin{aligned}g(x) &= Wx + b; \\f(x) &= \text{softmax}(g(x)).\end{aligned}$$

Another form:

$$\frac{\log P(y = i \mid x)}{\log P(y = j \mid x)} = \frac{w_i \cdot x + b_i}{w_j \cdot x + b_j}$$

Logistic regression: 2 classes

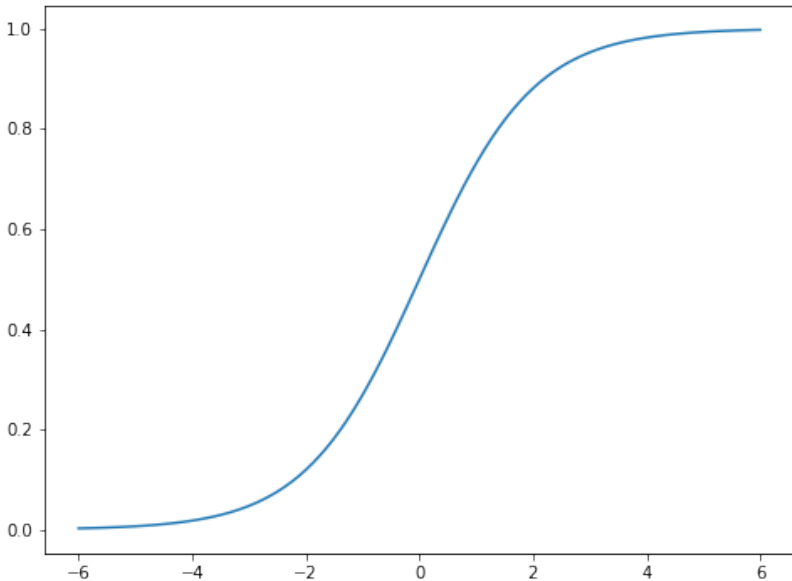
$$f_1(x) = \frac{\exp(w_1 \cdot x + b_1)}{\exp(w_1 \cdot x + b_1) + \exp(w_2 \cdot x + b_2)} =$$

$$\frac{1}{1 + \exp((w_2 - w_1) \cdot x + b_2 - b_1)} =$$

$$\frac{1}{1 + \exp(w' \cdot x + b')} =$$

$$\text{sigmoid}(w' \cdot x + b').$$

Logistic regression: 2 classes



$$\mathcal{L}(w) = \sum_i \mathbb{I}[y_i = 1] \log(1 + \exp(wx_i + b)) + \mathbb{I}[y_i = 0] \log(1 + \exp(-wx_i - b))$$

- has no analytical solution;
- smooth and convex.

Gradient Descent

$$\begin{aligned} f(\theta) &\rightarrow \min; \\ \theta^* &= \arg \min_{\theta} f(\theta). \end{aligned}$$

$$\begin{aligned} \theta^{t+1} &= \theta^t - \alpha \nabla f(\theta^t); \\ \theta^t &\rightarrow \theta^*, t \rightarrow \infty; \end{aligned}$$

Gradient Descent

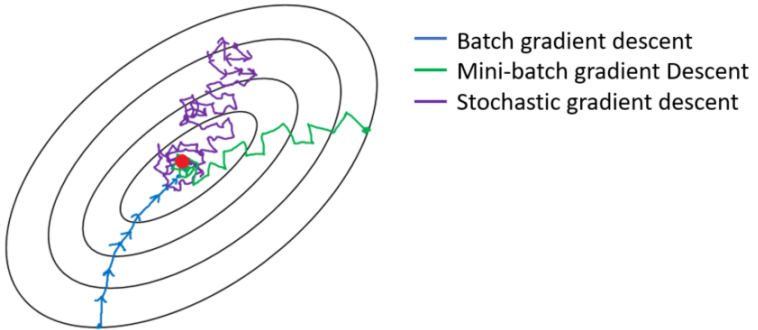
```
1:  $\theta := \text{initialization}$   
2: for  $t := 1, \dots$  do  
3:    $\theta := \theta - \alpha \nabla f(\theta^t)$   
4: end for
```

Stochastic Gradient Descent

$$f(\theta) = \sum_{i=1}^N f_i(\theta)$$

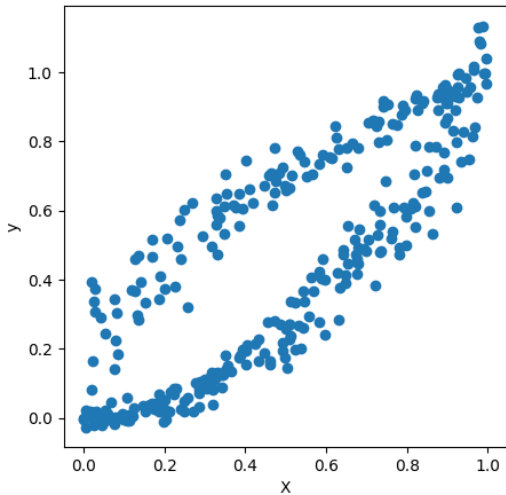
```
1:  $\theta :=$  initialization  
2: for  $t := 1, \dots$  do  
3:    $i := \text{random}(1, \dots, N)$   
4:    $\theta := \theta - \alpha \nabla f_i(\theta^t)$   
5: end for
```

Illustration

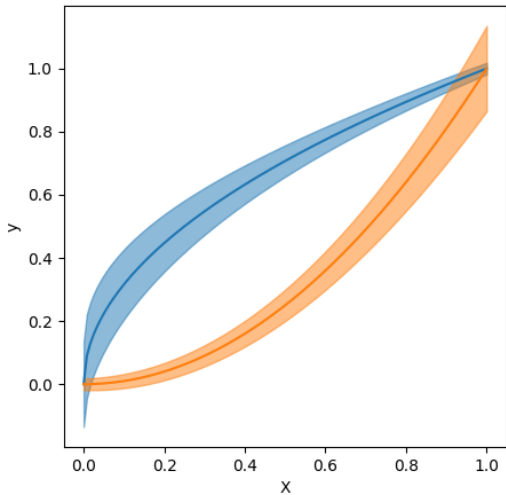


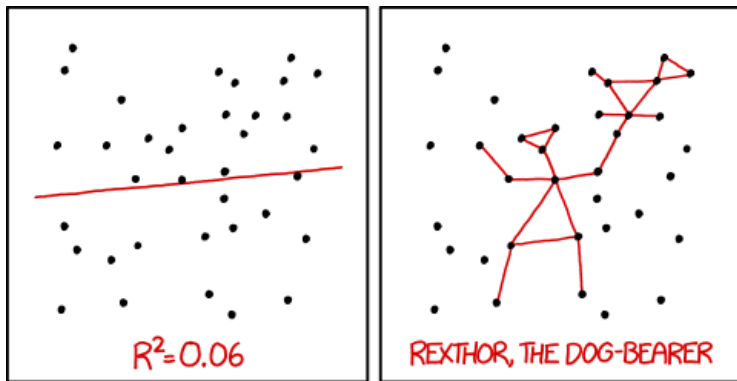
Source: towardsdatascience.com

Tricky example



Tricky example





I DON'T TRUST LINEAR REGRESSIONS WHEN IT'S HARDER
TO GUESS THE DIRECTION OF THE CORRELATION FROM THE
SCATTER PLOT THAN TO FIND NEW CONSTELLATIONS ON IT.

My first neural network

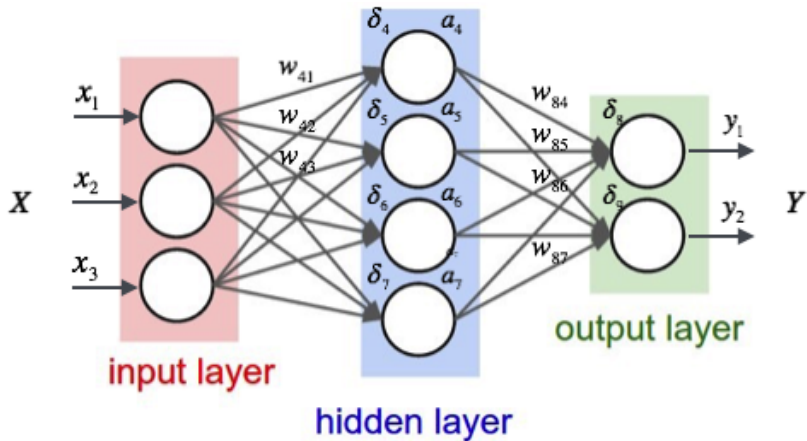
Universal Approximation Theorem

If ϕ is a non-constant, continuous, bounded, monotonic function, then every continuous function f on a compact set from \mathbb{R}^n can be approximated with any precision $\varepsilon > 0$ by:

$$g(x) = c + \sum_{i=1}^N \alpha_i \phi(w_i \cdot x + b_i)$$

given large enough N .

Universal Approximators



How to train a neural network

Stochastic Gradient Descent and Co.

How to train a neural network

Stochastic Gradient Descent and Co.

- how to initialize?
- how to choose an appropriate learning rate?
- how many units?
- which activation function to choose?