

Statistical Methods for Data Science: A Starter Kit

Yinan Yu

yinan@chalmers.se/yinan.yu@asymptotic.ai

Statistical Data Type (I1)

Categorical data: labels or tags

- Nominal: unordered labels, e.g. species of ducks
- Ordinal: ordered labels, e.g. {"duckling", "teen duck", "adult duck"}

Numerical data:

- Discrete (interval): countable, e.g. integers; numbers of ducks
- Continuous (ratio): uncountable, e.g. real values; weights of ducks

Data Container (I1)

Array (tensor):

- Scalar, vector, matrix, higher order array
- Same numerical data type
- Python library: numpy

Table:

- Described by columns and rows
- Mixed data types
- Python library: pandas

Descriptive Statistics: numerical data (I1)

Data set (a sample): numerical data x_1, \dots, x_N

Centrality:

- sample mean: $\bar{x} = \frac{1}{N} \sum_{i=1}^N x_i$
- median: sort x_i and median is the value in the middle
- mode (discrete values): the most frequent value in a sample

Dispersion:

- min, max, range: $\min\{x_i\}, \max\{x_i\}, \max\{x_i\} - \min\{x_i\}$
- quantiles/percentiles: given $p \in (0, 1)$, q is a p -quantile of the data if $p \times 100\%$ of the data are smaller than q

- sample variance: $s^2 = \frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^2$
- sample standard deviation: s

Dependence: given a data set with two paired values:

$$\{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$$

- covariance:

$$\text{cov}(x, y) = \frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})$$

- correlation: measures how close data is to a linear relationship

$$\text{corr}(x, y) = \frac{\text{cov}(x, y)}{\sigma_x \sigma_y}, \quad -1 \leq \text{corr}(x, y) \leq 1$$

Descriptive Statistics: categorical data (I1)

Data set (a sample): categorical data x_1, \dots, x_N


- Count/frequency
- Transformed into numerical, discrete data

Visualization: numerical data (I1)


- Distribution:

– Histogram/normalized histogram 

– Kernel density estimator 

– Box plot 


- Dependence (two variables):


– Scatter plot 

– Heat map for covariance/correlation 


Visualization: categorical data (I1)

- Distribution

– Bar chart 

– Pie chart 

- Dependence


– Mosaic plot 

Probability distribution (I2)


- Experiment: an action that leads to one outcome
- Sample space: the set of all possible outcomes from an experiment
- Event: a subset of the sample space
- Random variable (discrete/continuous): assigning a numerical value to each outcome of the experiment; denoted by capital letters, e.g. X
- Probability distribution: the probability of the occurrence of *any* event in the sample space; can be described by $P(\text{event})/\text{PDF}/\text{PMF}/\text{CDF}$
 - $P(\text{event})$: the probability of an event occurring
 - PDF $f(x)$: the probability density function for continuous random variables; $\int_{-\infty}^{+\infty} f(x) dx = 1$
 - PMF $f(x)$: the probability mass function for discrete random variables; $\sum_{x=-\infty}^{+\infty} f(x) = 1$
 - CDF $F(x)$: the cumulative density function; $F(x) = P(X \leq x)$
- Quantile function Q : the inverse CDF, i.e.
$$F_X(Q(p)) = p \text{ and } Q(F_X(q)) = q$$
- Conditional probability
- Independent and identically distributed (i.i.d.) random variables

Examples (12)


Discrete/continuous, PMF/PDF, parameters, typical use cases (statistical data type, example scenarios)

- Bernoulli distribution 

- Categorical distribution 

- Binomial distribution (18) 

- Discrete uniform 

- Gaussian distribution 

Generalize this learning routine to unknown distributions

Properties of Gaussian distributions (16)

- Let $X \sim \mathcal{N}(\mu_X, \sigma_X^2)$ be a Gaussian random variable, then the following random variables are also Gaussian
 - Scaling: $tX \sim \mathcal{N}(t\mu_X, t^2\sigma_X^2)$, $t \neq 0$ is a constant
 - Translation: $X + c \sim \mathcal{N}(\mu_X + c, \sigma_X^2)$, c is a constant
 - $tX + c \sim \mathcal{N}(t\mu_X + c, t^2\sigma_X^2)$
- Let $X \sim \mathcal{N}(\mu_X, \sigma_X^2)$ and $Y \sim \mathcal{N}(\mu_Y, \sigma_Y^2)$ be two **independent** Gaussian random variables, then the following random variables are also Gaussian
 - $X + Y \sim \mathcal{N}(\mu_X + \mu_Y, \sigma_X^2 + \sigma_Y^2)$
 - $X - Y \sim \mathcal{N}(\mu_X - \mu_Y, \sigma_X^2 + \sigma_Y^2)$

Bayes' rule (14, 15)

- Parameter estimation:

$$f_{\Theta|data}(\theta | data) = \frac{\overbrace{f_{data|\Theta}(data | \theta)}^{\text{likelihood}} \overbrace{f_{\Theta}(\theta)}^{\text{prior}}}{f_{data}(data)}$$

where $f(\cdot)$ is the PDF/PMF

- Multinomial naive Bayes classifier:

$$P(Y = y | X = x) = \frac{\overbrace{P(X = x | Y = y)}^{\text{likelihood}} \overbrace{P(Y = y)}^{\text{prior}}}{P(X = x)}$$

- Gaussian naive Bayes classifier/Gaussian mixture models:

$$P(Y = y | X = x) = \frac{\overbrace{f_{X|Y=y}(x | Y = y)}^{\text{likelihood}} \overbrace{P(Y = y)}^{\text{prior}}}{f_X(x)}$$

Q-Q plot (13)

- Use cases:
 - Compare a data distribution to a theoretical distribution (one sample test)
 - Compare two data distributions (two sample test)
- Steps:
 - Choose a set of m probabilities $p_1, \dots, p_m \in [0, 1]$ (make sure they spread evenly between 0 and 1)
 - For $i = 1, 2, \dots, m$:
 - * Compute the quantile q_i^1 of the first distribution at p_i
 - * Compute the quantile q_i^2 of the second distribution at p_i
 - * Make a scatter plot of the pair (q_i^1, q_i^2)
- Interpretation
 - Case 1: if the two distributions are identical, the points in the Q-Q plot should follow a 45° straight line $y = x$
 - Case 2: if the two distributions are linearly related, the points in the Q-Q plot follow a straight line that is not necessarily $y = x$
 - Case 3: if the two distributions are from different families of distributions, the points in the Q-Q plot are not lying on a straight line.

Mathematical Modeling (13)

$$y = g(x; \theta | h)$$

1. What do we want to predict, i.e. what is the target y ?
2. What are the variables x ?
3. What is the mathematical function g that relates variables x to the target y ?
4. Are there any hyperparameters h in the function g ? How do we choose them?
5. What are the unknown parameters θ in g ? **How do we estimate them from data?**

Parameter estimation (14)

- Maximum likelihood estimation: frequentist approach - **θ is deterministic** (constant)
- Maximum A Posteriori estimation: Bayesian approach - **θ is probabilistic** (random)

Maximum Likelihood Estimation (14)

Given a model $y = g(x; \mathcal{O} \mid h)$, where \mathcal{O} is a set of parameters

- Describe the experiments
- Describe the data generated from the experiments
- Describe the random variables (typically with i.i.d. assumption)
- Choose a parameter of interest $\theta \in \mathcal{O}$
- Choose the maximum likelihood estimation as the estimation method:
Given data x_1, \dots, x_N and assume i.i.d. random variables X_i with PDF/PMF $f(x_i)$,

$$L(\theta \mid x_1, \dots, x_N) = \prod_{i=1}^N f(x_i; \theta)$$

- Compute $\hat{\theta}_{MLE}$ by maximizing the likelihood function:

$$\begin{aligned}\hat{\theta}_{MLE} &= \arg \max_{\theta} L(\theta \mid x_1, \dots, x_N) \\ &= \arg \max_{\theta} \prod_{i=1}^N f(x_i; \theta)\end{aligned}$$

or equivalently, minimizing the **negative log likelihood function**:

$$\hat{\theta}_{MLE} = \arg \min_{\theta} - \sum_{i=1}^N \log(f(x_i; \theta))$$

- Simple case, e.g. i.i.d. Gaussian, find the closed-form solution by:
 - Taking the partial derivative with respect to the parameter
 - Setting the derivative to zero
 - Solving for the parameter
- In general, the estimate needs to be found by iterative methods, e.g. gradient descent

Maximum A Posteriori Estimation (14)

Given a model $y = g(x; \mathcal{O} \mid h)$, where \mathcal{O} is a set of parameters

- Describe the experiments
- Describe the data generated from the experiments
- Describe the random variables (typically with i.i.d. assumption)
- Choose a parameter of interest $\theta \in \mathcal{O}$
- Choose the maximum a posteriori estimation as the estimation method
 - θ is assumed to be drawn from a random distribution**
 - Choose a prior distribution for θ along with the hyperparameters: $f_{\Theta}(\theta)$
 - Prior might be known by the problem setup
 - If prior unknown, conjugate priors are typically chosen for various reasons
 - Find the likelihood function: $f_{X|\Theta}(\mathbf{x} \mid \theta)$ (same as in MLE)
 - Express the posterior distribution in terms of the prior and the likelihood function

$$f_{\Theta|X}(\theta \mid \mathbf{x}) = \frac{f_{X|\Theta}(\mathbf{x} \mid \theta) f_{\Theta}(\theta)}{f_X(\mathbf{x})}$$

- Compute $\hat{\theta}_{MAP}$ by maximizing the posterior function (or equivalently, minimizing the negative log posterior function without the normalization constant). The optimal solution can be found by a closed-form expression or using iterative techniques.

Standardization (16)

Standardization: let X be a random variable that follows **any probability distribution** with mean μ and standard deviation σ . The standardization of X is

$$Y = \frac{X - \mu}{\sigma}$$

Central limit theorem (16)

Given an i.i.d. sample X_1, X_2, \dots, X_N from **ANY probability distribution** with *finite mean μ and variance σ^2* (most distributions satisfy this!), when the sample size N is sufficiently large, the **sample mean** approximately follows a Gaussian distribution with mean μ and variance $\frac{\sigma^2}{N}$, i.e.

$$\bar{X} \sim \mathcal{N}(\mu, \frac{\sigma^2}{N})$$

Confidence interval (16)

- **Data:** x_1, \dots, x_N
- **Random variable:** X_1, \dots, X_N with i.i.d. assumption
- **Parameter of interest:** θ , e.g. the mean μ
- **Estimate:** $\hat{\theta}$, e.g. the sample mean \bar{x}
- **Confidence interval** for a given confidence level $1 - \alpha$ (e.g. 95%)

– Definition:

$$\text{confidence interval} = (\hat{\theta} - \text{margin of error}, \hat{\theta} + \text{margin of error})$$

where

$$\text{margin of error} = \text{critical value} \times \text{standard error of } \hat{\theta}$$

– Calculation:

Distribution of X_i	Scenario	θ	$\hat{\theta}$ (sampling distribution)	Critical value	Standard error	Confidence interval	Note
i.i.d. Gaussian	σ known	mean	sample mean \bar{x}	$z_{\alpha/2}$	$\frac{\sigma}{\sqrt{N}}$	$\left(\bar{x} - z_{\alpha/2} \frac{\sigma}{\sqrt{N}}, \bar{x} + z_{\alpha/2} \frac{\sigma}{\sqrt{N}}\right)$	exact
	σ unknown		(Gaussian distribution)	$t_{\alpha/2}$	$\frac{s}{\sqrt{N}}$	$\left(\bar{x} - t_{\alpha/2} \frac{s}{\sqrt{N}}, \bar{x} + t_{\alpha/2} \frac{s}{\sqrt{N}}\right)$	
i.i.d.	σ known		sample mean \bar{x}	$z_{\alpha/2}$	$\frac{\sigma}{\sqrt{N}}$	$\left(\bar{x} - z_{\alpha/2} \frac{\sigma}{\sqrt{N}}, \bar{x} + z_{\alpha/2} \frac{\sigma}{\sqrt{N}}\right)$	approximate
	σ unknown		(approximately Gaussian under CLT)	$t_{\alpha/2}$	$\frac{s}{\sqrt{N}}$	$\left(\bar{x} - t_{\alpha/2} \frac{s}{\sqrt{N}}, \bar{x} + t_{\alpha/2} \frac{s}{\sqrt{N}}\right)$	for large N
i.i.d.	-	any	MLE (asymptotically Gaussian cf. 14)	$z_{\alpha/2}$	$\frac{1}{\sqrt{N I_N(\hat{\theta})}}$	$\left(\hat{\theta} - z_{\alpha/2} \frac{1}{\sqrt{N I_N(\hat{\theta})}}, \hat{\theta} + z_{\alpha/2} \frac{1}{\sqrt{N I_N(\hat{\theta})}}\right)$	asymptotic
i.i.d.	-	any	any statistic (any distribution)	bootstrap the error quantile		$\left(\hat{\theta} - \epsilon_{1-\alpha/2}, \hat{\theta} - \epsilon_{\alpha/2}\right)$	approximate

Hypothesis testing steps (17)

- Step 1 Make a “boring” statement, i.e. the default explanation
- Step 2 Design an **experiment**
- Step 3 Describe the **data** generated from the experiment and the corresponding random variables
- Step 4 Describe the parameter of interest and their estimates
- Step 5 Translate the “boring” statement into a statistical hypothesis and call it the **null hypothesis H_0**
- Step 6 Find the expression for the **test statistic s**
- Step 7 Find the expression for the **null distribution**
- Step 8 Define **an alternative hypothesis H_A** : one-tailed or two-tailed
- Step 9 Choose a **significance level α** (the tail), which defines the **rejection region**
- Step 10 Collect **data**
- Step 11 Compute the test statistic from data
- Step 12 Compute the p -value
- Step 13 If $p\text{-value} < \alpha$, i.e. the test statistic falls in the rejection region of the null distribution, then we reject the hypothesis H_0 ; otherwise, we fail to reject H_0 .

Statistical tests (18)

	Data discrete/continuous	No. of samples used in the test	Remark	Test statistic	Null distribution
One-sample z-test	Continuous	1	σ known	$\frac{\bar{x}-c}{\sigma/\sqrt{N}}$	Standard Gaussian
One-sample t-test	Continuous	1	σ unknown	$\frac{\bar{x}-c}{s/\sqrt{N}}$	Student's-t distribution
Two-sample z-test	Continuous	2	σ_X, σ_Y known	$\frac{\bar{x}-\bar{y}-c}{\sqrt{\frac{\sigma_X^2}{N_X} + \frac{\sigma_Y^2}{N_Y}}}$	Standard Gaussian
Two-sample t-test	Continuous	2	σ_X, σ_Y unknown	$\frac{\bar{x}-\bar{y}-c}{\sqrt{\frac{s_X^2}{N_X} + \frac{s_Y^2}{N_Y}}}$	Student's-t distribution
Paired t-test	Continuous	1 or 2 (paired)	σ_X, σ_Y unknown	$\frac{m_{X-Y}-c}{s_{X-Y}/\sqrt{N}}$	Student's-t distribution
Binomial test (exact)	Discrete	1	Small N	k_0	Binomial distribution
Binomial test (approximate)	Discrete	1	Large N	$\frac{k_0 - N\pi}{\sqrt{N\pi(1-\pi)}}$	Standard Gaussian
McNemar's test (exact)	Discrete	1 (2 groups)	Small $n_{01} + n_{10}$	$\min(n_{01}, n_{10})$	Binomial distribution
McNemar's test (approximate)	Discrete	1 (2 groups)	Large $n_{01} + n_{10}$	$\frac{(n_{01} - n_{10} - 1)^2}{n_{01} + n_{10}}$	Chi-squared distribution

Machine learning: classification

Multinomial naive Bayes classifier (15)

- **Prediction y :** categorical data $y \in \{1, \dots, C\}$
- **Variables $x_i, i = 1, \dots, n$:** categorical data $x_i \in V$, where V is the vocabulary $V = \{w_1, \dots, w_K\}$ given K unique categories
 - **Assumptions:**
 - * x_i 's are independent - **NAIVE!**
 - * x_i follows a categorical distribution

Note: here n is the size of the input data, e.g. the length of a document

- **Model g :**

$$\hat{y} = g(x_1, \dots, x_n) = \arg \max_{c \in \{1, \dots, C\}} P(c) \prod_{i=1}^n P(x_i | c)$$

where $P(c)$ is the prior and $\prod_{i=1}^n P(x_i | c)$ is the likelihood under the assumptions

- **Hyperparameters h :** smoothing factor α , e.g. $\alpha = 1$
- **Parameters θ :** $P(c)$, V (if not given) and $P(w_i | c)$ for all $w_i \in V$
- **Parameter estimation (training):** given the vocabulary $V = \{w_k\}_{k=1}^K$ and a training data set $\{(b_1, y_1), \dots, (b_N, y_N)\}$, where each b_j contains a list of words. Let $N_c = \text{count}(y_j = c)$.
 - Likelihood $P(w_i | c)$ for each w_i :

$$P(w_i | c) = \frac{\text{count}(\forall w_i \in b_j \text{ for } y_j = c) + \alpha}{\text{count}(\forall \text{ words} \in \text{class } c) + \alpha K}$$

- Prior $P(c)$:

$$P(c) = \frac{N_c}{N}$$

Gaussian naive Bayes classifier (15)

- **Prediction y :** categorical data $y \in \{1, \dots, C\}$
- **Variables $x_i, i = 1, \dots, d$:** continuous numerical data $x_i \in \mathbb{R}$
 - **Assumption:**
 - * x_i 's are independent - **NAIVE!**
 - * x_i follows a Gaussian distribution
- **Model g :**

$$\begin{aligned} \hat{y} &= g(x_1, \dots, x_d) \\ &= \arg \max_{c \in \{1, \dots, C\}} P(c) \prod_{i=1}^d f_i(x_i | y = c) \end{aligned}$$

where $P(c)$ is the prior and $\prod_{i=1}^d f_i(x_i | y = c)$ is the likelihood under the assumptions with $f_i(x_i | y = c) = \frac{1}{\sqrt{2\pi\sigma_{c,i}^2}} e^{-\frac{(x_i - \mu_{c,i})^2}{2\sigma_{c,i}^2}}$

- **Parameters θ :** $P(c)$, $\mu_{c,i}$, $\sigma_{c,i}$ in $f_i(x_i | y = c)$ for all c and i
- **Parameter estimation (training):** given a training data set $\{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_N, y_N)\}$, where each $\mathbf{x}_j = [x_1^j, \dots, x_d^j]$ is a vector containing all the features for one data point. Let $N_c = \text{count}(y_j = c)$.
 - $\mu_{c,i}$, $\sigma_{c,i}$ in the likelihood $f_i(x_i | y = c)$ for all variable i and all classes c :

$$\hat{\mu}_{c,i} = \frac{1}{N_c} \sum_{t=1}^{N_c} x_i^t$$

$$\hat{\sigma}_{c,i} = \sqrt{\frac{1}{N_c - 1} \sum_{t=1}^{N_c} (x_i^t - \hat{\mu}_{c,i})^2}$$

for all $t \in \text{class } c$

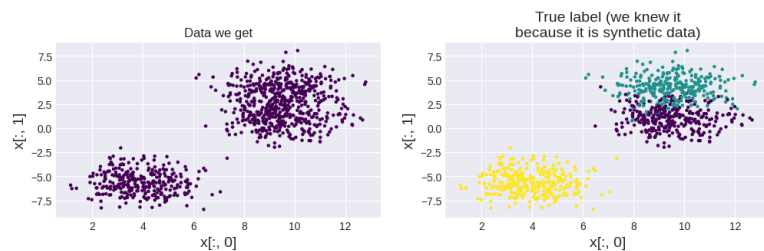
- Prior $P(c)$:

$$P(c) = \frac{N_c}{N}$$

Machine learning: clustering

K-means (19)

- **Prediction** y : categorical data $y \in \{1, \dots, K\}$
- **Variables** x : d dimensional feature vector x



- **Model**:

$$y = \arg \min_{k \in \{1, \dots, K\}} \text{dist}(x, \mu_k)$$

where $\text{dist}(\cdot, \cdot)$ is a distance measure; in this course, we use the Euclidean distance; it is **hard clustering** - one data point is assigned to only one cluster

- **Hyperparameters**: K
- **Parameters**: K centroids
- **Parameter estimation**: an iterative method to update the centroids until convergence
 - Randomly choose K centroids $\hat{\mu}_k$ for $k = 1, \dots, K$, e.g. randomly choose K data points from \mathcal{X}
 - Repeat the two steps below until convergence, e.g. $\hat{\mu}_k$ does not change anymore
 - * For all $i = 1, \dots, N$, assign x_i to a cluster \hat{k}_i by computing

$$\hat{k}_i = \arg \min_{k \in \{1, \dots, K\}} \text{dist}(x_i, \hat{\mu}_k)$$

- * Let \mathcal{X}_k be the set of all x_i assigned to cluster k and N_k be the size of \mathcal{X}_k , compute

$$\hat{\mu}_k \leftarrow \frac{1}{N_k} \sum_{x_j \in \mathcal{X}_k} x_j$$

Gaussian Mixture Models (110, 111)

- **Prediction** y : y can be a set of continuous numerical data K posterior probabilities or categorical data $y \in \{1, \dots, K\}$
- **Variables** x : a d dimensional feature vector $x = [x_1, \dots, x_d]$ with PDF $f(x) = \sum_{k=1}^K \pi_k f(x | k)$
- **Model**: for $k = 1, \dots, K$

$$\underbrace{P(k | x)}_{\text{posterior}} = \frac{\underbrace{P(k)}_{\text{prior}} \underbrace{f(x | k)}_{\text{likelihood of } k \text{ given data}}}{\sum_{c=1}^K P(c) f(x | c)}$$

It is **soft clustering** - x is assigned to **all clusters** with a probability - the posterior $P(k | x)$; **alternatively**, y can be defined as the cluster index with the highest posterior probability, i.e.

$$y = \arg \max_{k \in \{1, \dots, K\}} P(k | x) = \arg \max_{k \in \{1, \dots, K\}} P(k) f(x | k)$$

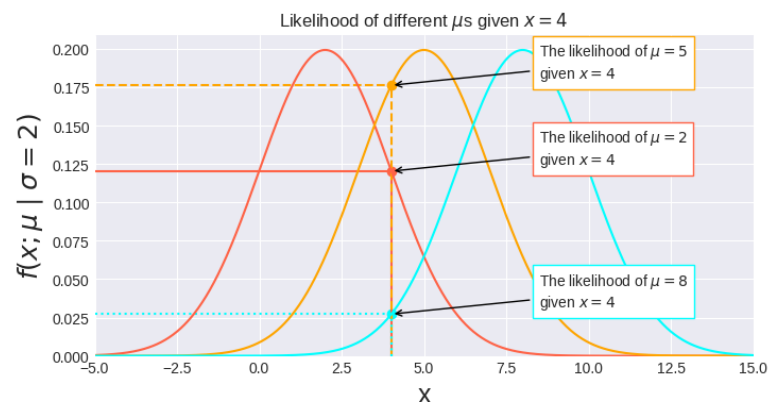
- **Hyperparameters**: K
- **Parameters**: the parameters of the mixture distribution $f(x)$
 - The parameters for each Gaussian likelihood $f(x | k)$
 - The prior $P(k)$, typically denoted as π_k
- **Parameter estimation**: the Expectation-Maximization algorithm

What is a likelihood function (14)

- Intuitively, the **likelihood** describes **how likely** the **observed data points** are generated from **a given probability distribution**
- If data is not modeled by probability distributions, there is no likelihood
- Graphically, in a PDF/PMF plot, **data** is on the **x-axis** and the **likelihood** is on the **y-axis**
- If **data** is discrete, **likelihood** = the probability
- If **data** is continuous, **likelihood** != the probability
- The **likelihood function**: $L(\theta | x) = f(x; \theta)$
- Note: we use Gaussian distributions for illustration purposes

Likelihood of μ Given One Observation x (14)

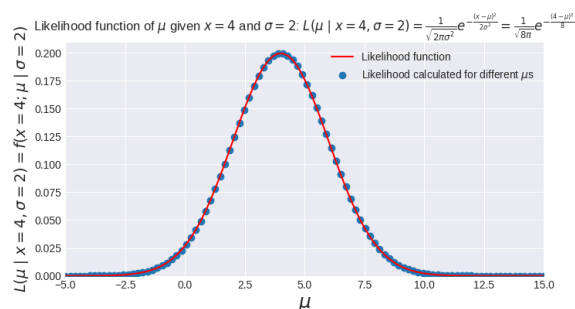
Likelihood of μ given data $x = 4$: $f(x = 4; \mu | \sigma = 2)$:



Likelihood Function Given One Observation x (14)

Likelihood function of μ given data $x = 4$ for $-\infty \leq \mu \leq \infty$:

$$\begin{aligned} L(\mu | x = 4, \sigma = 2) &= f(x = 4; \mu | \sigma = 2) \\ &= \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} = \frac{1}{\sqrt{8\pi}} e^{-\frac{(4-\mu)^2}{8}} \end{aligned}$$



PDF, Probability, Likelihood, Likelihood Function (14)

Probability density function	
Probability of events	
Likelihood of a parameter given data	
Likelihood function of a parameter given data	
Maximum likelihood estimation	

Likelihood of μ Given N Observations x_1, \dots, x_N (14)

Assumption: random variables X_i are **independent and identically distributed (i.i.d.)** random variables

- X_1, \dots, X_N are independent:

$$f_{X_1, \dots, X_N}(x_1, \dots, x_N) = f_{X_1}(x) \cdots f_{X_N}(x)$$

- X_1, \dots, X_N are identically distributed - they have the same PDF:

$$f_{X_1}(x; \mu | \sigma) = \cdots = f_{X_N}(x; \mu | \sigma) = f(x; \mu | \sigma)$$

where $\sigma = \sigma_1 = \sigma_2 = \cdots = \sigma_N$ and $\mu = \mu_1 = \mu_2 = \cdots = \mu_N$.

The likelihood function can be expressed as:

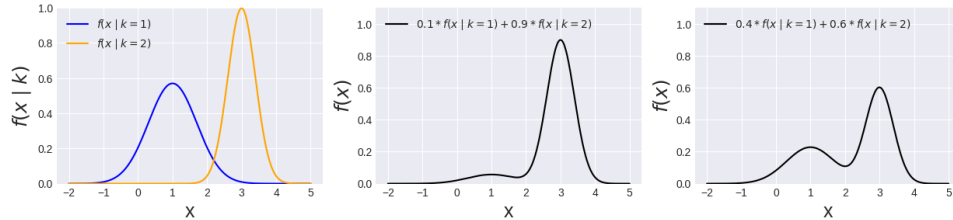
$$\begin{aligned} L(\mu | x_1 = 6.98, x_2 = 5.43, \dots, x_{20} = 7.27, \sigma = 2) \\ &= f(x_1 = 6.98, x_2 = 5.43, \dots, x_{20} = 7.27; \mu | \sigma = 2) \\ &= f(6.98; \mu | \sigma = 2) f(5.43; \mu | \sigma = 2) \cdots f(7.27; \mu | \sigma = 2) \\ &= \frac{1}{\sqrt{8\pi}} e^{-\frac{(6.98-\mu)^2}{8}} \frac{1}{\sqrt{8\pi}} e^{-\frac{(5.43-\mu)^2}{8}} \cdots \frac{1}{\sqrt{8\pi}} e^{-\frac{(7.27-\mu)^2}{8}} \\ &= \left(\frac{1}{\sqrt{8\pi}} \right)^{20} e^{-\frac{(6.98-\mu)^2 + \cdots + (7.27-\mu)^2}{8}} \end{aligned}$$

Likelihood of A Mixture Model Given One Observations x (110)

Parameters: π_k (prior), μ_k , σ_k , for all $k = 1, \dots, K$

$$f(x) = \sum_{k=1}^K \pi_k f(x | k)$$

where $f(x | k)$ is Gaussian PDF with parameters μ_k and σ_k



Likelihood of A Mixture Model Given N Observations x_1, \dots, x_N (110)

Parameters: π_k (prior), μ_k , σ_k , for all $k = 1, \dots, K$

$$f_{X_1, \dots, X_N}(x_1, \dots, x_N) \stackrel{i.i.d.}{=} \prod_{i=1}^N f(x_i) = \prod_{i=1}^N \sum_{k=1}^K \pi_k f(x | k)$$

Symbols and notations

- Generic mathematical symbol
 - Integral (area under the curve between a and b): $\int_a^b f(x)dx$
 - Summation: $\sum_{i=1}^N x_i = x_1 + x_2 + \dots + x_N$
 - Product: $\prod_{i=1}^N x_i = x_1 \times x_2 \times \dots \times x_N$
 - Factorial: $n! = n \times (n-1) \times \dots \times 1$
 - Probability of an event: $P(\text{event})$
 - $[a, b]$: the range from a to b , where a and b are numerical values
 - $\{a, b, \dots\}$: a set that contains elements a, b, \dots
 - Mean value: μ
 - Standard deviation: σ
- Symbols specific in this course
 - N : sample size; number of data points in a data set
 - N_X : size of sample X
 - Chonker duck: a duck that is very round and probably overweight