Chapter II: Basics from Linear Algebra, Probability Theory, and Statistics

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Chapter II

II.1 Linear Algebra

Vectors, Matrices, Eigenvalues, Eigenvectors, Singular Value Decomposition

II.2 Probability Theory

Events, Probabilities, Random Variables, Distributions, Bounds, Limit Theorems

II.3 Statistical Inference

Parameter Estimation, Confidence Intervals, Hypothesis Testing

II.3 Statistical Inference

- **1.** Parameter Estimation
- 2. Confidence Intervals
- 3. Hypothesis Testing

Based on LW Chapters 6, 7, 9, 10

Statistical Model

- A statistical model *M* is a set of distributions (or regression functions), e.g., all unimodal smooth distributions
- *M* is called a **parametric model** if it can be completely described by a finite number of parameters, e.g., the family of Normal distributions for a finite number of parameters μ and σ

$$M = \left\{ f_X(x;\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \mid \mu \in \mathbb{R}, \ \sigma > 0 \right\}$$

Statistical Inference

- Given a parametric model M and a sample X_1, \ldots, X_m , how do we infer (learn) the parameters of M?
- For multivariate models with observed variable *X* and response variable *Y*, this is called **prediction** or **regression**, for a discrete outcome variable this is also called **classification**

Idea of Sampling



- <u>Example</u>: Suppose we want to estimate the average salary of employees in German companies
 - Sample 1: Suppose we look at n = 200 top-paid CEOs of major banks
 - Sample 2: Suppose we look at n = 1,000 employees across all sectors

Basic Types of Statistical Inference

- Given independent and identically distributed (iid.) samples $X_1, \ldots, X_n \sim X$ of an unknown distribution X
 - e.g.: *n* single-coin-toss experiments $X_1, ..., X_n \sim \text{Bernoulli}(p)$
- Parameter estimation
 - e.g.: what is the parameter p of Bernoulli(p)? what is E[X], the cdf F_X of X, the pdf f_X of X, etc.?
- Confidence intervals
 - e.g.: give me all values C = [a, b] such that $P[p \in C] \ge 0.95$ with interval boundaries *a* and *b* derived from samples $X_1, ..., X_n$

• Hypothesis testing

• e.g.: $H_0: p = 1/2$ (i.e., coin is fair) vs. $H_1: p \neq 1/2$

1. Parameter Estimation

- A **point estimator** for a parameter θ of a probability distribution X is a random variable $\hat{\theta}_n$ derived from an iid. sample X_1, \ldots, X_n
- <u>Examples</u>:
 - Sample mean $\bar{X} := \frac{1}{n} \sum_{i=1}^{n} X_i$ • Sample variance $S_X^2 := \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \bar{X})^2$
- An estimator $\hat{\theta}_n$ for parameter θ is **unbiased** if $E[\hat{\theta}_n] = \theta$

otherwise the estimator has **bias** $E[\hat{\theta}_n] - \theta$

• An estimator on sample size *n* is **consistent** if

$$\lim_{n \to \infty} P[|\hat{\theta}_n - \theta| < \epsilon] = 1 \text{ for any } \epsilon > 0$$

Estimation Error

- Let $\hat{\theta}_n$ be an estimator for parameter θ over iid. samples X_1, \ldots, X_n
- The distribution of $\hat{\theta}_n$ is called **sampling distribution**
- The standard error for $\hat{\theta}_n$ is: $se(\hat{\theta}) = \sqrt{Var(\hat{\theta}_n)}$
- The mean squared error (MSE) for $\hat{\theta}_n$ is:

$$MSE(\hat{\theta}_n) = E[(\hat{\theta}_n - \theta)^2] = bias^2(\hat{\theta}_n) + Var(\hat{\theta}_n)$$

• The estimator $\hat{\theta}_n$ is asymptotically Normal if

 $(\hat{\theta}_n - \theta)/se$ converges in distribution to N(0,1)

Types of Estimation

• Non-Parametric Estimation

- **no assumptions** about the model *M* nor the parameters θ of the underlying distribution *X*
- e.g.: "plug-in estimators" (e.g., histograms) to approximate X
- Parametric Estimation
 - requires assumptions about the model M and the parameters θ of the underlying distribution X
 - analytical or numerical methods for estimating θ
 - Method of Moments
 - Maximum Likelihood
 - Expectation Maximization (EM)

Empirical Distribution Function

• The **empirical distribution function** \hat{F}_n is the cdf that puts probability mass 1/n at each data point X_i

$$\hat{F}_n(x) = \frac{1}{n} \sum_{i=1}^n \mathbb{I}(X_i \le x)$$

with indicator function

$$\mathbb{I}(X_i \le x) = \begin{cases} 1 & : & X_i \le x \\ 0 & : & X_i > x \end{cases}$$

- A statistical function ("statistics") T(F) is any function over F, e.g., mean, variance, skewness, median, quantiles, correlation
- The plug-in estimator of $\theta = T(F)$ is $\hat{\theta}_n = T(\hat{F}_n)$

Histograms as Density Estimators

Instead of the full empirical distribution, often compact synopses can be used, such as histograms where X₁, ..., X_n are grouped into *m* cells (buckets) c₁, ..., c_m with bucket boundaries *lb*(c_i) and *ub*(c_i)

$$lb(c_1) = -\infty$$
, $ub(c_m) = \infty$, $ub(c_{i-1}) = lb(c_i)$ for $(1 \le i \le m)$, and
 $freq_f(c_i) = \hat{f}_n(x) = \frac{1}{n} \sum_{j=1}^n \mathbb{I}(lb(c_i) < X_j \le ub(c_i))$
 $freq_F(c_i) = \hat{F}_n(x) = \frac{1}{n} \sum_{j=1}^n \mathbb{I}(X_j \le ub(c_i))$
• Example:



Method of Moments

- Suppose parameter $\theta = (\theta_1, ..., \theta_k)$ has k components
- Compute *j*-th moment for $1 \le j \le k$:

$$\alpha_j = \alpha_j(\theta) = E_{\theta}[X^j] = \int_{-\infty}^{+\infty} x^j f_X(x) \, dx$$

• Compute *j*-th sample moment for $1 \le j \le k$:

$$\hat{\alpha}_j = \frac{1}{n} \sum_{i=1}^n X_i^j$$

• Method-of-moments estimate of θ is obtained by solving a system of k equations in k unknowns

$$\alpha_1(\hat{\theta}_n) = \hat{\alpha}_1$$
$$\vdots$$
$$\alpha_k(\hat{\theta}_n) = \hat{\alpha}_k$$

Method of Moments (Example)

- Let $X_1, ..., X_n \sim \text{Normal}(\mu, \sigma^2)$. $\alpha_1 = E_{\theta}[X] = \mu$ $\alpha_2 = E_{\theta}[X^2] = Var(X) + (E[X])^2 = \sigma^2 + \mu^2$
- By solving the system of 2 equations in 2 unknowns

$$\hat{\mu} = \frac{1}{n} \sum_{i=1}^{n} X_i$$
$$\hat{\sigma}^2 + \hat{\mu}^2 = \frac{1}{n} \sum_{i=1}^{n} X_i^2$$

we obtain as solutions

$$\hat{\mu} = \bar{X}_n$$
 $\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X}_n)^2$

Maximum Likelihood

- Let X_1, \ldots, X_n be iid. with pdf $f(x;\theta)$
- Estimate parameter θ of a postulated distribution f(x;θ) such that the likelihood that the sample values x₁, ..., x_n are generated by the distribution are maximized
- Maximize $L(x_1, ..., x_n, \theta) \approx P[x_1, ..., x_n \text{ originate from } f(x; \theta)]$
- Usually formulated as:

$$\underset{\theta}{\operatorname{arg\,max}} L_n[\theta] = \prod_{i=1}^n f(X_i, \theta)$$

- The value $\hat{\theta}$ that maximizes $L_n[\theta]$ is called the **maximum-likelihood estimate (MLE)** of θ
- If analytically intractable, MLE can be determined using numerical iteration methods

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Maximum Likelihood (Example)

- Let $X_1, ..., X_n \sim \text{Bernoulli}(p)$ (corresponding to *n* coin tosses)
- Assume that we observed *h* times head and (*n*-*h*) times tail
- Maximum-likelihood estimation of parameter p

$$L[h, n, p] = \prod_{i=1}^{n} f(X_i; p) = \prod_{i=1}^{n} p^{X_i} (1-p)^{1-X_i} = p^h (1-p)^{(n-h)}$$

• Maximize log-likelihood function

$$\log L[h, n, p] = h \times \log(p) + (n - h) \times \log(1 - p)$$
$$\frac{\partial L}{\partial p} = \frac{h}{p} - \frac{n - h}{1 - p} = 0 \quad \Rightarrow \quad p = \frac{h}{n}$$

Maximum Likelihood for Normal Distributions

$$L(x_1, \dots, x_n, \mu, \sigma^2) = \left(\frac{1}{\sqrt{2\pi\sigma}}\right)^n \prod_{i=1}^n e^{-\frac{(x_i - \mu)^2}{2\sigma^2}}$$

$$\frac{\partial L}{\partial \mu} = \frac{-1}{2\sigma^2} \sum_{i=1}^{n} 2(x_i - \sigma) = 0$$

$$\frac{\partial L}{\partial \sigma^2} = -\frac{n}{2\sigma^2} + \frac{1}{2\sigma^4} \sum_{i=1}^n (x_i - \mu)^2 = 0$$

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

2. Confidence Intervals

• Determine interval estimator T for parameter θ such that $P[T - a \le \theta \le T + a] = 1 - \alpha$

T±*a* is the **confidence interval** and 1-*a* the **confidence level**

- For the distribution of a random variable *X*, a value x_{γ} ($0 < \gamma < 1$) is with $P[X \le x_{\gamma}] \ge \gamma$ and $P[X \ge x_{\gamma}] \ge 1-\gamma$ is called γ -quantile
 - the 0.5-quantile is known as **median**
 - for the standard Normal distribution N(0,1) the γ -quantile is denoted Φ_{γ}
- For a given a <u>or</u> α, find a value z of N(0,1) that denotes the [T-a,T+a] confidence interval <u>or</u> a corresponding γ-quantile for 1-α



Confidence Intervals for Expectations (I)

- Let $X_1, ..., X_n$ be a sample from a distribution X with unknown expectation μ and known variance σ^2
- For sufficiently large *n*, the sample mean \overline{X} is N(μ , σ^2/n) distributed and

$$P[-z \leq \frac{(X-\mu)\sqrt{n}}{\sigma} \leq z] = \Phi(z) - \Phi(-z)$$

$$= \Phi(z) - (1 - \Phi(z))$$

$$= 2\Phi(z) - 1$$

$$= P[\bar{X} - \frac{z\sigma}{\sqrt{n}} \leq \mu \leq \bar{X} + \frac{z\sigma}{\sqrt{n}}]$$

$$\Rightarrow P[\bar{X} - \frac{\Phi_{1-\alpha/2}\sigma}{\sqrt{n}} \leq \mu \leq \bar{X} + \frac{\Phi_{1-\alpha/2}\sigma}{\sqrt{n}}] = 1 - \alpha$$



Confidence Intervals for Expectations (I) (cont'd)

$$P[\bar{X} - \frac{\Phi_{1-\alpha/2}\sigma}{\sqrt{n}} \le \mu \le \bar{X} + \frac{\Phi_{1-\alpha/2}\sigma}{\sqrt{n}}] = 1 - \alpha$$

• For confidence interval $[\bar{X} - a, \bar{X} + a]$ compute

$$z = \frac{a\sqrt{n}}{\sigma}$$
 and lookup $\Phi(z)$ to determine 1- α

• For **confidence level** $1-\alpha$ set

$$z = \Phi_{1-\frac{\alpha}{2}}$$
 (i.e., as (1- $\alpha/2$)-quantile of N(0,1))
then $a = \frac{z \sigma}{\sqrt{n}}$ to determine
confidence interval



Confidence Intervals for Expectations (I) (Example)

- Based on a random sample of n = 100 queries, we observe an average response time of $\bar{X} = 64$. We further know that the standard deviation is $\sigma = 4$
- Q: What is the confidence of the interval 64 ± 0.5 ?

$$a = 0.5$$

$$z = \frac{0.5\sqrt{100}}{4} = 1.25$$

$$\Phi(1.25) = 0.89435$$

$$1 - \frac{\alpha}{2} = 0.89435$$

$$1 - \alpha = 0.7887$$

- <u>A</u>: 78.87%
- Q: What's the 99% confidence interval?

$$\begin{array}{rcrcrcr}
1 - \alpha &=& 0.99 \\
\alpha &=& 0.01 \\
a &=& \frac{\Phi_{0.005} \times 4}{\sqrt{100}} = 1.032
\end{array}$$

<u>A</u>: 64±1.032

Confidence Intervals for Expectations (II)

- Let X₁, ..., X_n be an iid. sample from a distribution X with unknown expectation μ, unknown variance σ², but known sample variance S²
- For sufficiently large *n*, the random variable

$$T = \frac{(\bar{X} - \mu)\sqrt{n}}{S}$$

has a **Student's** *t* **distribution** with (n-1) degrees of freedom

$$f_{T,n}(t) = \frac{\Gamma(\frac{n+1}{2})}{\Gamma(\frac{n}{2})\sqrt{n\pi}\left(1+\frac{t^2}{n}\right)^{\frac{n+1}{2}}}$$

with the Gamma function

$$\Gamma(x) = \int_0^\infty e^{-t} t^{x-1} dt \quad \text{for} \quad x > 0$$

Confidence Intervals for Expectations (II) (cont'd)

$$P[\bar{X} - \frac{t_{n-1,1-\alpha/2}S}{\sqrt{n}} \le \mu \le \bar{X} + \frac{t_{n-1,1-\alpha/2}S}{\sqrt{n}}] = 1 - \alpha$$

• For confidence interval $[\bar{X} - a, \bar{X} + a]$ compute

$$t = \frac{a\sqrt{n}}{S}$$
 and lookup $f_{T(n-1)}(t)$ to determine 1- α

• For **confidence level** $1-\alpha$ set

$$t = t_{n-1,1-\alpha/2}$$
 (i.e., as (1- $\alpha/2$)-quantile of $f_{T(n-1)}$)
then $a = \frac{t S}{\sqrt{n}}$ to determine
confidence interval



3. Hypothesis Testing

- Suppose we throw a coin *n* times and want to know whether the coin is fair, i.e., P(H) = P(T)
- Let $X_1, \ldots, X_n \sim \text{Bernoulli}(p)$ be the iid. coin flips, so that the coin is fair if p = 0.5
- Let the **null hypothesis** H₀ be "the coin is fair"
- The alternative hypothesis H₁ is then "the coin is not fair"

Normal Distribution Table $T_{0} = 1$

The Normal Distribution Functions $\Phi(z) = \int_{-\infty}^{z} \frac{e^{-t^{2}/2}}{\sqrt{2\pi}} dt$ 7 0.04 0.05 0.06 0.07 0.03 0.08 0.09 0.02 0.01 .51595 .51994 52790 .50399 83 .54380 .54776 .55172 .55567 .55962 .56356 .56749 .57142 .57535

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Hypothesis Testing Terminology

- $\theta = \theta_0$ is called a simple hypothesis
- $\theta > \theta_0$ or $\theta < \theta_0$ is called a **compound hypothesis**
- $H_0: \theta = \theta_0$ vs. $H_1: \theta \neq \theta_0$ is called a **two-sided test**
- $H_0: \theta \le \theta_0 \text{ vs. } H_1: \theta > \theta_0 \text{ and } H_0: \theta \ge \theta_0 \text{ vs. } H_1: \theta < \theta_0$ are called a **one-sided test**
- **Rejection region** R : if $X \in R$, reject H₀ otherwise retain H₀
- The rejection region is typically defined using a **test statistic** *T* and a **critical value** *c*

$$R = \{ X : T(X) > c \}$$

p-Values

- The *p*-value is the probability that **if H**₀ **holds**, we observe values **at least as extreme** of the test statistic
 - It is not the probability that H₀ holds
 - The **smaller** the *p*-value, the **stronger** is the evidence against H₀, i.e., if we observe a small enough *p*-value, we can reject H₀
 - How small the *p*-value needs to be depends on the application
- Typical *p*-value scale:
 - < 0.01 very strong evidence against H₀
 - 0.01 0.05 strong evidence against H₀
 - 0.05 0.10 weak evidence against H₀
 - > 0.1 little or no evidence against H_0

Types of Errors & Statistical Significance

	Retain H ₀	Reject H ₀
H ₀ true	ОК	Type I Error
H ₁ true	Type II Error	OK

- Hypothesis tests often performed at a level of significance α
 - means that H_0 is rejected if the *p*-value is less than α
 - reported as "results is statistically significant at the α level"
 - specifying *p*-values is more informative
- Don't confuse statistical significance with practical significance
 - e.g.: "blue hyperlinks increase click rate by 0.0001% over black ones" "fuel consumption is reduced by 0.0001 l/km by new part"

. . .

The Wald Test

- Two-sided test for $H_0: \theta = \theta_0$ vs. $H_1: \theta \neq \theta_0$
- Test statistic $W = \frac{|\hat{\theta} \theta_0|}{\hat{se}}$ with sample estimate $\hat{\theta}$ and $\hat{se} = se(\hat{\theta}) = \sqrt{Var(\hat{\theta})}$
- *W* converges in probability to N(0, 1)
- If w is the observed value of the Wald statistic, the p-value is 2Φ(-|w|)

The Wald Test (Example)

- We can use the Wald test to test if our coin is fair
 - Suppose the **observed sample mean** is 0.6 and the **observed standard error** is 0.049
 - We obtain as a test statistic value $w = (0.6 0.5) / 0.049 \approx 2.04$
 - The *p*-value is therefore 2Φ(-|2.04|) ≈ 0.042 (i.e., a fair coin would lead to such an extreme value *w* only with probability 0.042), which gives us strong evidence to reject the null hypothesis H₀



Pearson's χ^2 Test for Multinomial Data

- Let $X_1, \ldots, X_m \sim \text{Multinomial}(n, \mathbf{p})$, the MLE of \mathbf{p} is $(X_1/n, X_2/n, \ldots, X_n/n)$
- Let $\mathbf{p}_0 = (p_{01}, p_{02}, ..., p_{0n})$ and we want to test H₀ : $\mathbf{p} = \mathbf{p}_0$ vs. H₁ : $\mathbf{p} \neq \mathbf{p}_0$
- Pearson's χ^2 statistic is

$$T = \sum_{j=1}^{k} \frac{(X_j - n p_{0j})^2}{n p_{0j}} = \sum_{j=1}^{k} \frac{(X_j - E_j)^2}{E_j}$$

with expected value $E_j = E[X_j] = n p_{0j}$ of X_j under H₀

• The *p*-value is $P(\chi^2_{k-1} > t)$ where *t* is the observed value of the test statistic and there are (*k*-1) degrees of freedom

Pearson's χ^2 Test for Multinomial Data (Example)

- We can use Pearson's χ^2 test to test whether a dice is fair
 - Suppose after 1,000 throws of the dice, we observed
 ① x 173, ② x 167, ③ x 167, ④ x 176, ⑤ x 167, ⑥ x 150
 => p = (0.173, 0.167, 0.167, 0.176, 0.167, 0.150) (based on MLE)
 - $\mathbf{p}_0 = (0.167, 0.167, 0.167, 0.167, 0.167, 0.167)$
 - $T = 2.43 \Rightarrow p$ -value is 0.80 giving us no evidence to reject H₀

																	• •	A	nzahl der	Wahrsche	einlichkeit	$p = \alpha$	10			
														•	. •	• • '		g	rade m	0,99	0,98	0,95	0,90	0,80	0,70	0,50
ahl der heits-	χ ² _α Wahrsch	einlichkeit	Abb. 1. $p = \alpha$	4					• •	•	•	• •	•	•					1 2 3	0,00016 0,020 0,115	0,0006 0,040 0,185	0,0039 0,103 0,352	0,016 0,211 0,584	0,064 0,446 1,005	0,148 0,713 1,424	0,455 1,386 2,366
: //	0,99 0,00016 0,020 0,115 0,30 0,87 1,24 2,09 2,56 2,09 2,56 4,1 4,7 5,8 6,4	0,98 0,0006 0,100 0,185 0,43 0,73 1,13 1,56 2,53 3,06 4,2 4,8 5,4 6,6 7,3 7,9	0,95 0,0039 0,103 0,352 0,71 1,14 1,63 2,17 2,73 3,32 3,94 4,6 5,2 5,9 6,6 7,3 8,0 8,7	0,90 0,016 0,211 0,584 1,06 1,61 2,20 2,83 3,49 4,17 4,86 5,6 6,3 7,0 7,8 8,5,6 9,3 10,1	0,80 0,064 0,446 1,005 2,34 3,07 3,82 4,59 5,38 6,18 7,0 7,8 8,6 8,6 8,6 9,5 10,3 11,2 12,0	0,70 0,148 0013 1,424 2,19 3,00 3,63 4,67 5,53 6,39 7,27 8,1 9,0 9,9 9,9 10,8 11,7 12,6 13,5 14,4	0,50 0,455 1,386 2,366 3,36 4,35 5,3 6,35 7,34 8,34 9,34 10,3 11,3 11,3 11,3 11,3 13,3 14,3 15,3 16,3	0,30 1,07 2,41 3,67 4,9 6,1 7,2 8,4 9,5 10,7 11,8 12,9 14,0 15,1 16,2 17,1 16,2 17,1 18,4 19,5 10,7 19,1 19,5	0,20 1,64 3,22 4,64 6,00 7,3 8,6 9,8 11,00 12,2 13,4 14,64 6,00 7,3 8,6 9,8 11,00 12,2 13,4 14,84 15,8 17,00 18,25 20,5 21,64 20,5 21,64 20,5 21,56 21,57	0,10 2,7 4,6 6,3 7,8 9,2 10,6 12,0 13,4 14,7 16,0 17,3 18,5 19,8 21,1 22,3 5 23,5 24,8 24,8	0,05 3,8 6,0 7,8 9,5 11,1 12,6 14,1 14,1 14,1 14,3 19,7 21,0 22,4 23,7 25,0 26,3 27,6	0,02 5,4 7,8 9,8 11,7 13,4 5,0 16,6 18,2 19,7 21,2 22,6 24,1 25,5 26,9 28,3 29,6 31,0 31,0	0,01 6,6 9,2 11,3 15,1 16,8 18,5 20,1 21,7 23,2 24,7 24,7 26,2 27,7 29,1 30,6 32,0 33,4 8	0,005 7,9 10,6 12,8 14,9 16,8 13,5 20,3 22,0 23,6 25,2 26,8 28,3 29,8 31,3 32,8 34,3 35,7 27	0,002 9,5 12,4 14,8 16,9 20,7 22,6 24,3 26,1 27,7 29,4 30,9 32,5 34,0 35,6 37,1 38,6 40,1	0,001 10,83 13,8 16,3 18,5 20,5 24,3 26,1 27,9 29,6 31,3 32,6 12,9 34,5	•••	•••	4 5 6	0,30 0,55 0,87	0,43 0,75 1,13	0,71 1,14 1,63	1,06 1,61 2,20	1,65 2,34 3,07	2,19 3,00 3,83	3,36 4,35 5,35



Pearson's χ^2 Test of Independence

- Pearson's χ^2 test can also be used to test if two random variables *X* and *Y* are independent
- Let X_1, \ldots, X_n and Y_1, \ldots, Y_n be the two samples
- Divide outcomes into *r* (for *X*) and *c* (for *Y*) disjoint intervals
- Populate *r*-by-*c* table O with frequencies, so that O_{lk} tells how many (X_i, Y_i) pairs have values *l*-th and *k*-interval respectively
- Assuming independence (H₀) the expected value of O_{lk} is

$$E_{lk} = \frac{\sum_{i=1}^{c} O_{li} \sum_{j=1}^{r} O_{jk}}{\sum_{j=1}^{r} \sum_{i=1}^{c} O_{ij}}$$

Pearson's χ^2 Test of Independence (cont'd)

• The value of the test statistic is

$$\chi^2 = \sum_{i=1}^{c} \sum_{j=1}^{r} \frac{(O_{ij} - E_{ij})^2}{E_{ij}}$$

• There are (r-1)(c-1) degrees of freedom

Summary of II.3

- Statistical inference based on a sample from a population
- **Empirical distribution function** and **histograms** as non-parametric estimation methods
- Method of moments and maximum likelihood as parametric estimation methods
- Confidence intervals
- Wald test and Pearson's χ^2 test for hypothesis testing

Normal Distribution Table

The Normal Distribution Functions $\Phi(z) = \int_{-\infty}^{z} \frac{e^{-t^{2}/2}}{dt} dt$												
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	1											
						λ						
				li li								
				4	(z)'							
					0							
					0	2						
z	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09		
0.0	.50000	.50399	.50798	.51197	.51595	.51994	.52392	.52790	.53188	.53586		
0.1	.53983	.54380	.54776	.55172	.55567	.55962	.56356	.56749	.57142	.57535		
0.2	.57926	.58317	.58706	.59095	.59483	.59871	.60257	.60642	.61026	. 61409		
0.3	.61791	.62172	.62552	.62930	.63307	. 33683	.64058	.64431	.64803	. 65173		
0.4	.65542	.65910	.66276	.66640	.67003	.67364	.67724	.68082	.68439	.68793		
0.5	.69146	. 69497	. 69847	.70194	.70540	.70884	.71226	.71566	.71904	. 72240		
0.6	.72575	.72907	.73237	.73565	.73891	.74215	.74537	.74857	.75175	. 75490		
0.7	.75804	.76115	.76424	. 76730	. 77035	. 77337	. 11631	. 77935	. 78230	. 78524		
0.8	.78814	.79103	.79389	. 79673	. 79955	.80234	.80511	.80785	.81057	.81327		
0.9	.81594	.81859	.82121	.82381	.82637	.82894	.83147	.83378	05007	04214		
1.0	.84134	.84375	.84614	.84849	.85083	.85314	.85543	.85767	.85775	00214		
1.1	.86433	.86650	. 86884	.87076	00251	.67473	00417	.87700	09977	00147		
1.2	.88493	.88588	.88877	.87085	90000	01140	01700	01444	01621	91774		
1.3	.90320	.90490	. 70000	92344	97507	92647	02795	02022	93056	93189		
1.4	.91924	07010	07574	07400	93922	07947	94042	94179	94295	94408		
1.2	01520	01470	01770	01945	94950	05053	95154	95254	95352	95449		
1.0	05517	05477	95728	95818	95907	95994	96080	96164	96246	96327		
1.7	04407	94195	94542	96639	96712	96784	26856	.96926	.96995	.97962		
1.0	07128	97193	97257	.97320	.97381	.97441	.97500	.97558	.97615	.97670		
1.9	07725	97778	97931	.97882	.97932	97982	.98030	.98077	.98124	.98169		
2.0	98214	98257	98300	98391	.98382	.98422	.98461	.98500	28537	.98574		
2.1	98610	98615	.98679	.98713	.98745	.93778	.98809	.99840	.98870	.98899		
2.3	98928	.98956	.98983	.99010	.99036	.99031	.99086	.99111	.99134	.99158		
2.4	99180	.99202	.99224	.99245	.99266	.99286	.99305	.99324	.99343	.99361		
2.5	.99379	.99396	.99413	.99430	.99446	.99461	.99477	.99492	.99506	.99520		
2.6	.99534	.99547	.99560	,99573	.99585	.99598	.99609	.99621	.99632	. 99643		
2.7	.99653	.99664	.99674	.99683	.99693	.99702	.99711	.99720	.99728	.99736		
2.8	.99744	.99752	.99760	.99767	.99774	.99781	.99788	.99795	.99801	.99807		
2.9	.99813	.99819	.99825	.99831	.99836	.99811	.99846	.99851	.99856	.99861		
3.0	.99865	.99869	.99874	.99878	.99882	.99886	.99889	.99893	.99896	.99900		
3.1	.99903	.99906	.99910	.99913	.99916	.99918	.99921	.99924	.99926	.99929		
3.2	.99931	.99934	.99936	.99938	.99940	.99942	.99944	.99946	,77748	.99950		
3.3	.99952	.99953	.99955	. 99957	.99958	.99960	.99961	.99962	. 99964	.99965		
3.4	.99966	.99968	.99969	.99978	.99971	.99972	.99973	.99774	.99975	.99976		
3.5	.99977	.99978	.99978	.99979	.99980	.99981	.99981	.99982	.99983	.99983		
3.6	. 99984	.99985	.99985	.99986	.99986	,99987	.99987	.99988	.99998	.99989		
3.7	.99989	.99990	. 99990	.99990	. 99991	. 99991	.99992	. 99992	.99992	00005		
3.8	. 99993	. 90903	.99993	. 999994	. 99994	. 77774	. 99994	. 42442	.77775	. 77993		

χ^2 Distribution Table



Anzahl der Freiheits- grade m	Wahrsche	ahrscheinlichkeit $p = \alpha$														
	0,99	0,98	0,95	0,90	0,80	0,70	0,50	0,30	0,20	0,10	0,05	0,02	0,01	0,005	0,002	0,001
	0.00016	0.000.6	0.0039	0.016	0.064	0 148	0.455	1.07	1.64	2.7	3.8	5.4	6.6	7.9	9.5	10.83
2	0,020	0.040	0 103	0 211	0 446	0,713	1.386	2.41	3.22	4.6	6.0	7.8	9.2	10.6	12,4	13.8
3	0,115	0.185	0.352	0.584	1,005	1.424	2.366	3.67	4.64	6.3	7.8	9.8	11.3	12.8	14,8	16,3
4	0.30	0.43	0.71	1.06	1.65	2.19	3.36	4.9	6.0	7.8	9.5	11.7	13.3	14,9	16,9	18,5
5	0.55	0.75	1.14	1.61	2.34	3.00	4.35	6.1	7.3	9.2	11,1	13,4	15,1	16,8	18,9	20,5
6	0.87	1.13	1.63	2.20	3.07	3.83	5.35	7.2	8.6	10,6	12,6	15,0	16,8	18,5	20,7	22,5
7	1.24	1.56	2.17	2.83	3.82	4.67	6.35	8.4	9.8	12.0	14,1	16,6	18,5	20,3	22,6	24,3
8	1.65	2.03	2,73	3.49	4.59	5.53	7.34	9.5	11.0	13.4	15,5	18,2	20,1	22,0	24,3	26,1
9	2.09	2.53	3.32	4.17	5.38	6.39	8.34	10.7	12,2	14,7	16,9	19,7	21,7	23,6	26,1	27,9
10	2.56	3.06	3.94	4.86	6.18	7.27	9.34	11.8	13,4	16,0	18,3	21,2	23,2	25,2	27,7	29,6
11	3.1	3.6	4.6	5.6	7.0	8.1	10.3	12,9	14,6	17,3	19,7	22,6	24,7	26,8	29,4	31,3
12	3.6	4.2	5.2	6.3	7.8	9.0	11.3	14.0	15,8	18,5	21,0	24,1	26,2	28,3	30,9	32,9
13	4.1	4.8	5.9	7.0	8.6	9.9	12.3	15,1	17,0	19,8	22,4	25,5	27,7	29,8	32,5	34,5
14	4.7	5.4	6.6	7.8	9.5	10,8	13,3	16,2	18,2	21,1	23,7	26,9	29,1	31,3	34,0	36,1
15	5.2	6,0	7.3	8.5	10.3	11,7	14,3	17,3	19,3	22,3	25,0	28,3	30,6	32,8	35,6	37,7
16	5.8	6,6	8.0	9,3	11.2	12,6	15,3	18,4	20,5	23,5	26,3	29,6	32,0	34,3	37,1	39,3
17	6,4	7,3	8.7	10,1	12,0	13,5	16,3	19,5	21,6	24,8	27,6	31,0	33,4	35,7	38,6	40,8
18	7.0	7,9	9,4	10,9	12,9	14,4	17,3	20,6	22,8	26,0	28,9	32,3	34,8	37,2	40,1	42,3
19	7,6	8,6	10,1	11,7	13,7	15,4	18,3	21,7	23,9	27,2	30,1	33,7	36,2	38,6	41,6	43,8
20	8,3	9,2	10,9	12,4	14,6	16,3	19,3	22,8	25,0	28,4	31,4	35,0	37,6	40,0	43,0	45,3
21	8,9	9,9	11,6	13,2	15,4	17,2	20,3	23,9	26,2	29,6	32,7	36,3	38,9	41,4	44,5	46,8
22	9,5	10,6	12,3	14,0	16,3	18,1	21,3	24,9	27,3	30,8	33,9	37,7	40,3	42,8	45,9	48,3
23	10.2	11,3	13,1	14,8	17,2	19,0	22,3	26,0	28,4	32,0	35,2	39,0	41,6	44,2	47,3	49,7
24	10,9	12,0	13,8	15,7	18,1	19,9	23,3	27,1	29,6	33,2	36,4	40,3	43,0	45,6	48,7	51,2
25	11,5	12,7	14,6	16,5	18,9	20,9	24,3	28,2	30,7	34,4	37,7	41,6	44,3	46,9	50,1	52,6
26	12,2	13,4	15,4	17,3	19,8	21,8	25,3	29,2	31,8	35,6	38,9	42,9	45,6	48,3	51,6	54,1.
27	12,9	14,1	16,2	18,1	20,7	22,7	26,3	30,3	32,9	36,7	40,1	44,1	47,0	49,6	52,9	55,5
28	13.6	14.8	16.9	18.9	21.6	23.6	27.3	31.4	34.0	37,9	41,3	45,4	48,3	51,0	54,4	56,9

Student's t Distribution Table

