

14. Schätzung von Parametern

14.1 Forderungen an eine Schätzung

14.2 Beispiele für Stichprobenfunktionen

14.3 Die χ^2 -Verteilung

14.4 Die Methode der kleinsten Quadrate

14.5 Die *Maximum Likelihood* Methode

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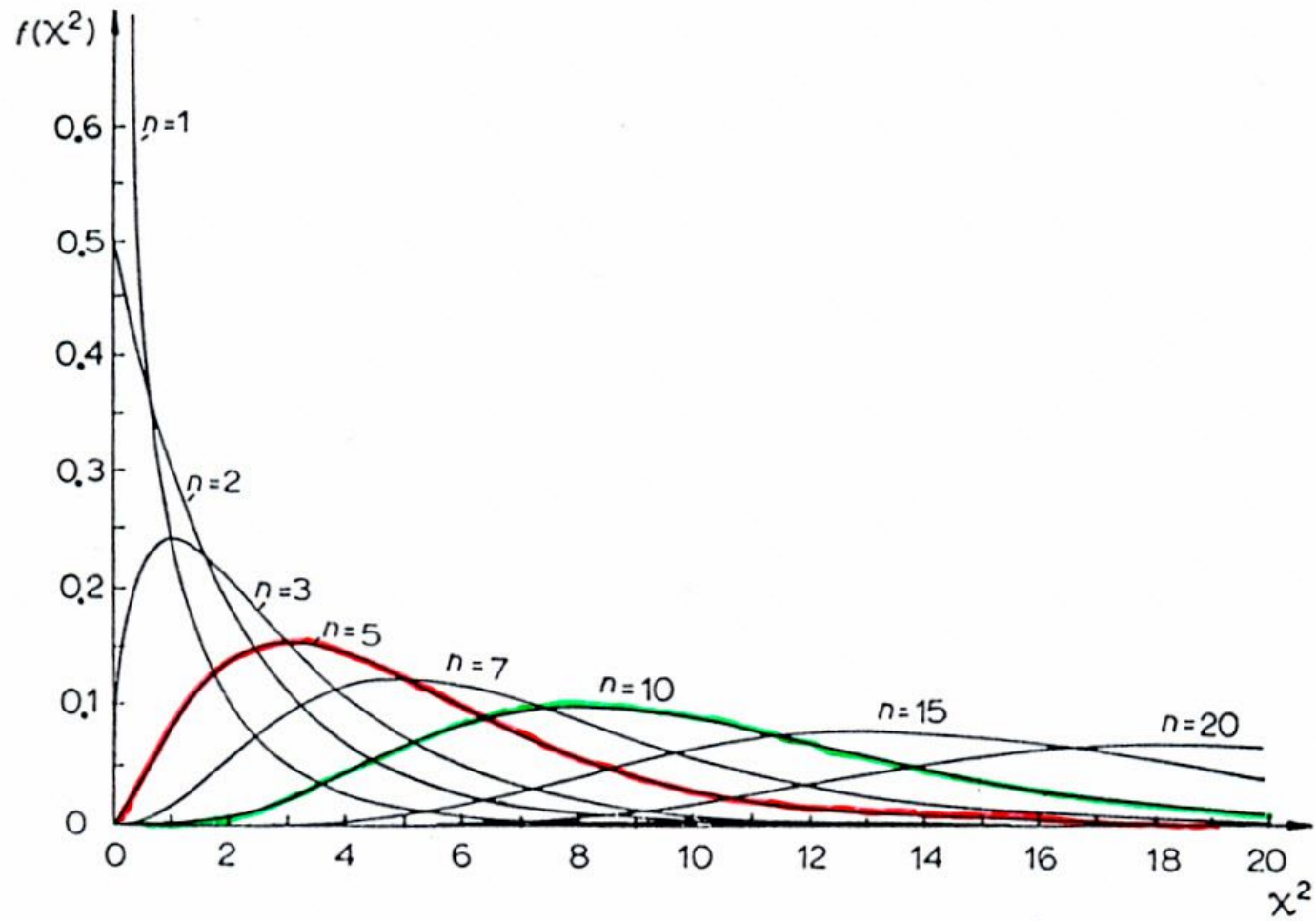


Bild 6.2 Wahrscheinlichkeitsdichte von χ^2 .

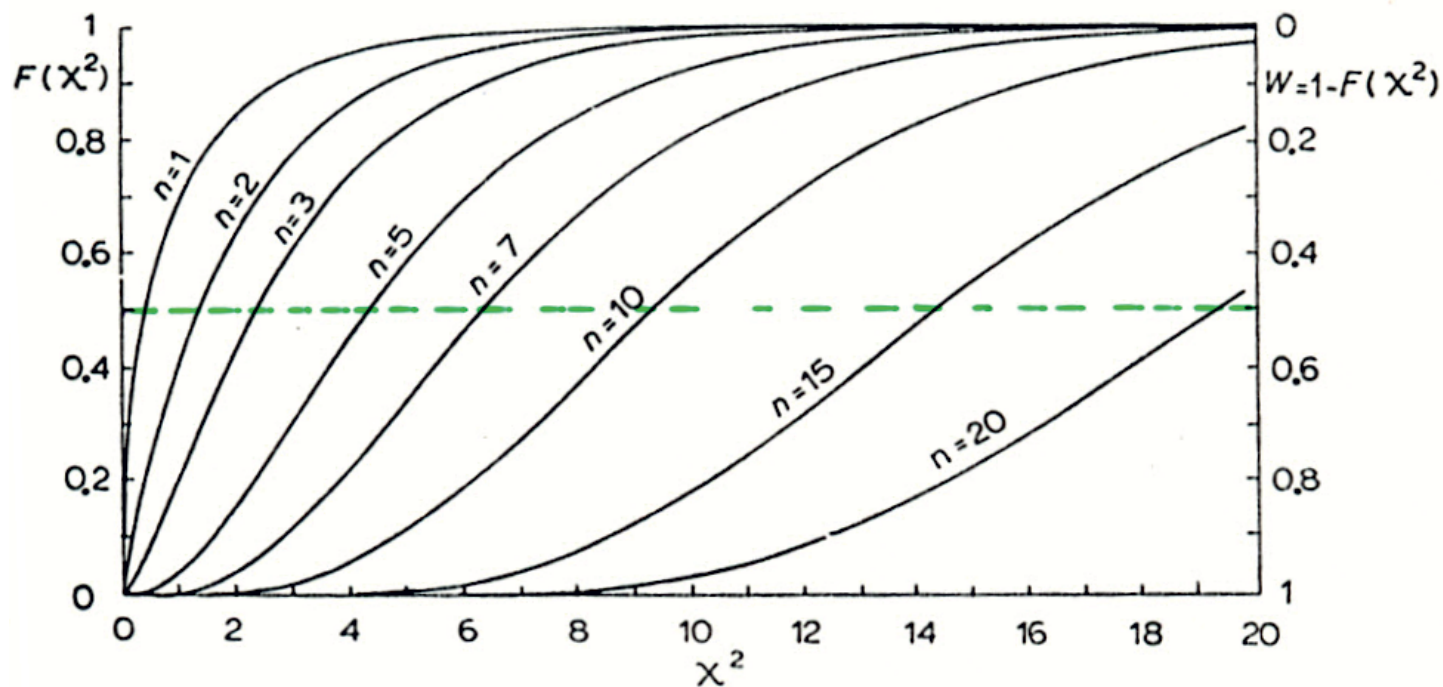
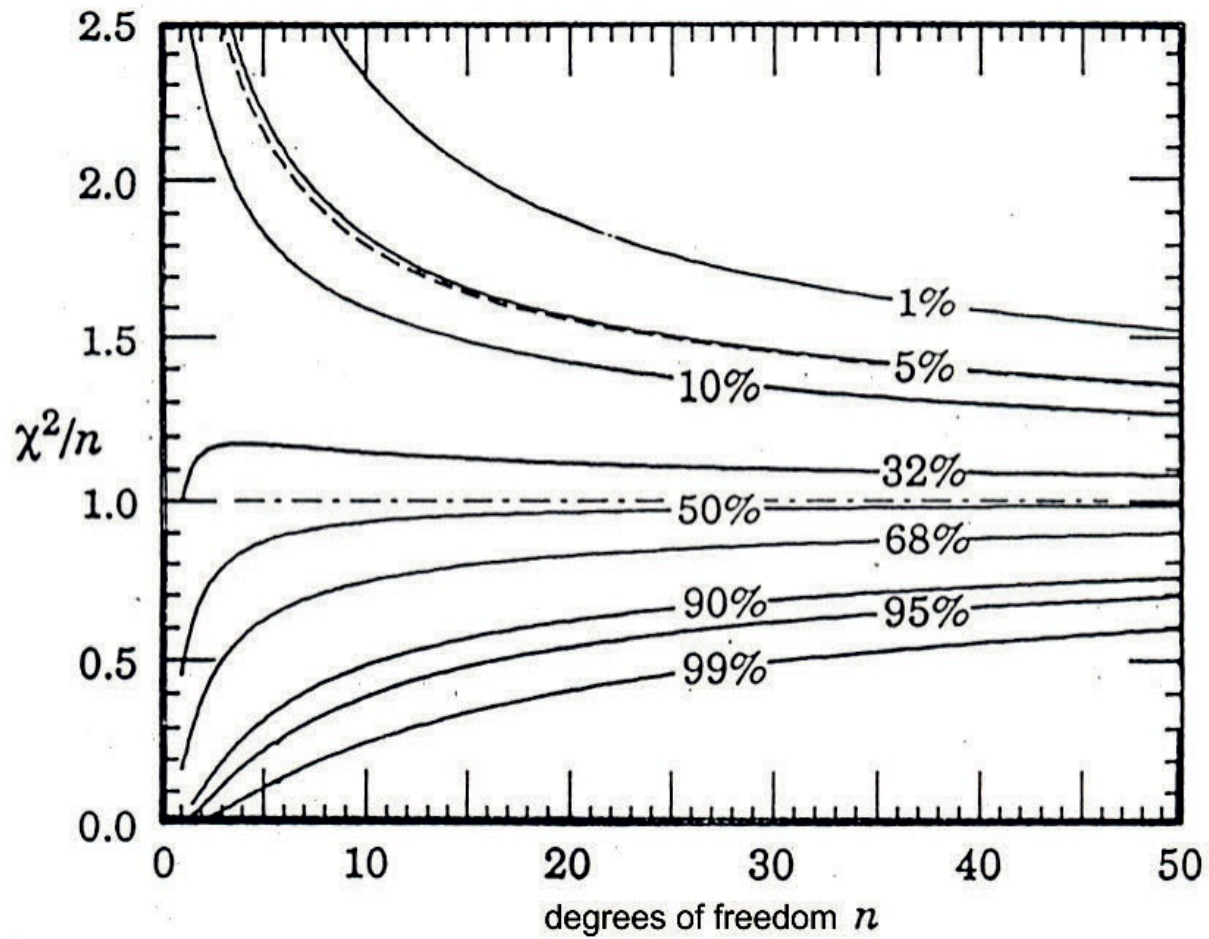


Bild 6.3 Verteilungsfunktion von χ^2 .

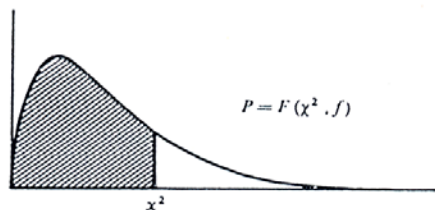


Tafel F - 4
 χ^2 -Verteilung.

Tafel F - 5
 Quantile der χ^2 -Verteilung.

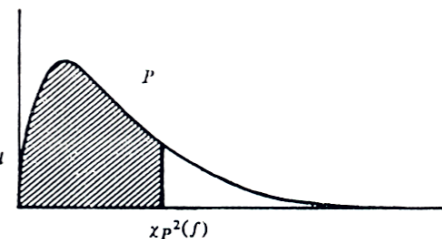
Tabelliert sind die Werte P , definiert durch

$$P = F(\chi^2, f) = \frac{1}{\Gamma(\frac{1}{2}f) 2^{\frac{1}{2}f}} \int_0^{\chi^2} u^{\frac{1}{2}f-1} e^{-\frac{1}{2}u} du$$



Tabelliert sind die Werte $\chi_p^2(f)$, definiert durch

$$P = \frac{1}{\Gamma(\frac{1}{2}f) 2^{\frac{1}{2}f}} \int_0^{\chi_p^2(f)} u^{\frac{1}{2}f-1} e^{-\frac{1}{2}u} du$$



χ^2	f									
	1	2	3	4	5	6	7	8	9	10
0.1	0.248	0.045	0.008	0.001	0.000	0.000	0.000	0.000	0.000	0.000
0.2	0.345	0.095	0.022	0.005	0.001	0.000	0.000	0.000	0.000	0.000
0.3	0.416	0.135	0.040	0.010	0.002	0.001	0.000	0.000	0.000	0.000
0.4	0.473	0.181	0.066	0.018	0.005	0.001	0.000	0.000	0.000	0.000
0.5	0.520	0.221	0.081	0.026	0.008	0.002	0.001	0.000	0.000	0.000
0.6	0.561	0.259	0.104	0.037	0.012	0.004	0.001	0.000	0.000	0.000
0.7	0.597	0.295	0.127	0.049	0.017	0.006	0.002	0.000	0.000	0.000
0.8	0.629	0.330	0.151	0.062	0.023	0.008	0.003	0.001	0.000	0.000
0.9	0.657	0.362	0.175	0.075	0.030	0.011	0.004	0.001	0.000	0.000
1.0	0.683	0.392	0.199	0.090	0.037	0.014	0.005	0.002	0.001	0.000
1.1	0.706	0.423	0.223	0.106	0.046	0.017	0.007	0.003	0.001	0.000
1.2	0.727	0.451	0.247	0.122	0.055	0.021	0.009	0.004	0.002	0.001
1.3	0.746	0.478	0.271	0.139	0.065	0.025	0.012	0.006	0.003	0.001
1.4	0.763	0.503	0.294	0.156	0.076	0.030	0.014	0.007	0.004	0.002
1.5	0.779	0.528	0.318	0.173	0.087	0.034	0.016	0.008	0.005	0.002
1.6	0.794	0.551	0.341	0.191	0.099	0.040	0.018	0.010	0.006	0.003
1.7	0.808	0.573	0.363	0.209	0.111	0.045	0.021	0.011	0.007	0.004
1.8	0.820	0.592	0.385	0.228	0.124	0.051	0.024	0.013	0.008	0.005
1.9	0.832	0.613	0.407	0.246	0.137	0.057	0.027	0.015	0.010	0.006
2.0	0.843	0.632	0.428	0.264	0.151	0.063	0.030	0.017	0.011	0.007
3.0	0.917	0.777	0.608	0.442	0.300	0.191	0.115	0.066	0.036	0.019
4.0	0.954	0.865	0.739	0.594	0.451	0.323	0.220	0.143	0.089	0.053
5.0	0.975	0.918	0.828	0.713	0.584	0.456	0.340	0.242	0.166	0.109
6.0	0.986	0.950	0.888	0.801	0.694	0.577	0.460	0.353	0.260	0.185
7.0	0.992	0.970	0.928	0.864	0.779	0.679	0.571	0.463	0.363	0.275
8.0	0.995	0.982	0.954	0.908	0.844	0.762	0.667	0.567	0.466	0.371
9.0	0.997	0.989	0.971	0.939	0.891	0.826	0.747	0.658	0.563	0.468
10.0	0.998	0.992	0.981	0.960	0.925	0.875	0.811	0.735	0.650	0.560
11.0	0.999	0.996	0.988	0.973	0.945	0.912	0.861	0.798	0.714	0.642
12.0	0.999	0.998	0.993	0.983	0.965	0.938	0.899	0.849	0.771	0.715
13.0	1.000	0.998	0.995	0.989	0.977	0.957	0.923	0.888	0.837	0.776
14.0	1.000	0.999	0.997	0.993	0.984	0.970	0.949	0.918	0.878	0.827
15.0	1.000	0.999	0.998	0.995	0.990	0.980	0.964	0.941	0.909	0.868
16.0	1.000	1.000	0.999	0.997	0.993	0.986	0.975	0.958	0.933	0.900
17.0	1.000	1.000	0.999	0.998	0.995	0.991	0.983	0.970	0.951	0.926
18.0	1.000	1.000	1.000	0.999	0.997	0.994	0.988	0.977	0.965	0.945
19.0	1.000	1.000	1.000	0.999	0.998	0.996	0.992	0.985	0.975	0.960
20.0	1.000	1.000	1.000	1.000	0.999	0.997	0.994	0.990	0.982	0.971

f	0.100	0.500	0.700	0.800	0.900	0.950	0.990	0.995	0.999
1	0.02	0.45	1.07	1.64	2.71	3.84	6.63	7.88	10.83
2	0.21	1.39	2.41	3.22	4.61	5.99	9.21	10.60	13.82
3	0.58	2.37	3.66	4.64	6.25	7.81	11.34	12.84	16.27
4	1.06	3.36	4.88	5.99	7.78	9.49	13.28	14.86	18.47
5	1.61	4.35	6.06	7.29	9.24	11.07	15.09	16.75	20.51
6	2.20	5.35	7.23	8.56	10.64	12.59	16.81	18.55	22.46
7	2.83	6.35	8.38	9.80	12.02	14.07	18.48	20.28	24.32
8	3.49	7.34	9.52	11.03	13.36	15.51	20.09	21.95	26.12
9	4.17	8.34	10.66	12.24	14.68	16.92	21.67	23.59	27.88
10	4.87	9.34	11.78	13.44	15.99	18.31	23.21	25.19	29.59
11	5.58	10.34	12.90	14.63	17.27	19.68	24.72	26.76	31.26
12	6.30	11.34	14.01	15.81	18.55	21.03	26.22	28.30	32.91
13	7.04	12.34	15.12	16.98	19.81	22.36	27.69	29.82	34.53
14	7.79	13.34	16.22	18.15	21.06	23.68	29.14	31.32	36.12
15	8.55	14.34	17.32	19.31	22.31	25.00	30.58	32.80	37.70
16	9.31	15.34	18.42	20.47	23.54	26.30	32.00	34.27	39.25
17	10.09	16.34	19.51	21.61	24.77	27.59	33.41	35.72	40.79
18	10.86	17.34	20.60	22.76	25.99	28.87	34.81	37.16	42.31
19	11.65	18.34	21.69	23.90	27.20	30.14	36.19	38.58	43.82
20	12.44	19.34	22.77	25.04	28.41	31.41	37.57	40.00	45.31
21	13.24	20.34	23.86	26.17	29.61	32.67	38.93	41.40	46.80
22	14.04	21.34	24.94	27.20	30.81	33.92	40.29	42.80	48.27
23	14.85	22.34	26.02	28.43	32.01	35.17	41.64	44.18	49.73
24	15.66	23.34	27.10	29.55	33.20	36.42	42.98	45.56	51.18
25	16.47	24.34	28.17	30.68	34.38	37.65	44.31	46.93	52.62
26	17.29	25.34	29.25	31.79	35.56	38.89	45.64	48.29	54.05
27	18.11	26.34	30.32	32.91	36.74	40.11	46.96	49.64	55.48
28	18.94	27.34	31.39	34.03	37.92	41.34	48.28	50.99	56.89
29	19.77	28.34	32.46	35.14	39.09	42.56	49.59	52.34	58.30
30	20.60	29.34	33.53	36.25	40.26	43.77	50.89	53.67	59.70
40	29.05	39.33	44.17	47.27	51.80	55.76	63.70	66.76	73.39
50	37.69	49.33	54.72	58.16	63.17	67.51	76.16	79.49	86.66
60	46.46	59.33	65.23	68.97	74.40	79.08	88.38	91.95	95.61
70	55.33	69.33	75.69	79.71	85.53	90.53	100.43	104.21	112.32
80	64.28	79.33	86.12	90.40	96.58	101.88	112.33	116.32	124.84
90	73.29	89.33	96.52	101.05	107.56	113.15	124.12	128.30	137.21
100	82.36	99.33	106.91	111.67	118.50	124.34	135.81	140.17	149.45

Beispiel: Ausgleichsgerade, Matrixschreibweise

$$y(x) = m \cdot x + c$$

$$= a_1 + a_2 \cdot x \quad \vec{\lambda} = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix}$$

n Meßpunkte
2 Parameter

$$H = \begin{pmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_n \end{pmatrix}$$

Annahme:
gleiche Fehler δ für alle Meßpunkte,
keine Korrelationen

$$\Rightarrow C = \begin{pmatrix} \delta^2 & 0 & \dots & 0 \\ 0 & \delta^2 & & \\ \vdots & & \ddots & \\ & & & \delta^2 \end{pmatrix}$$

Lösung:

$$\vec{\lambda} = (H^t C^{-1} H)^{-1} H^t C^{-1} \cdot \vec{y}$$

$$C = \delta^2 \cdot Id \Rightarrow \vec{\lambda} = \delta^2 (H^t H)^{-1} \frac{1}{\delta^2} H^t \cdot \vec{y}$$

$$\Leftrightarrow \vec{\lambda} = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} = \begin{pmatrix} \sum 1 & \sum x_i \\ \sum x_i & \sum x_i^2 \end{pmatrix}^{-1} \begin{pmatrix} \sum y_i \\ \sum x_i \cdot y_i \end{pmatrix}$$

$$= \frac{1}{n(\overline{x^2} - \bar{x}^2)} \begin{pmatrix} \overline{x^2} & -\bar{x} \\ -\bar{x} & 1 \end{pmatrix} \begin{pmatrix} \sum y_i \\ \sum x_i \cdot y_i \end{pmatrix}$$

$$\Rightarrow a_2 = \hat{m} = \frac{1}{n \cdot (\overline{x^2} - \bar{x}^2)} (-\bar{x} \cdot \sum y_i + 1 \cdot \sum x_i \cdot y_i) = \frac{-\bar{x}\bar{y} + \overline{xy}}{(\overline{x^2} - \bar{x}^2)}$$

Fehlermatrix der Parameter $\vec{\lambda}$: $C_\lambda = (H^t C^{-1} H)^{-1}$

$$= \delta^2 (H^t H)^{-1} = \frac{\delta^2}{n(\overline{x^2} - \bar{x}^2)} \begin{pmatrix} \overline{x^2} & -\bar{x} \\ -\bar{x} & 1 \end{pmatrix}$$

äquivalent zu Gleichungen aus Kap. 14.4.1

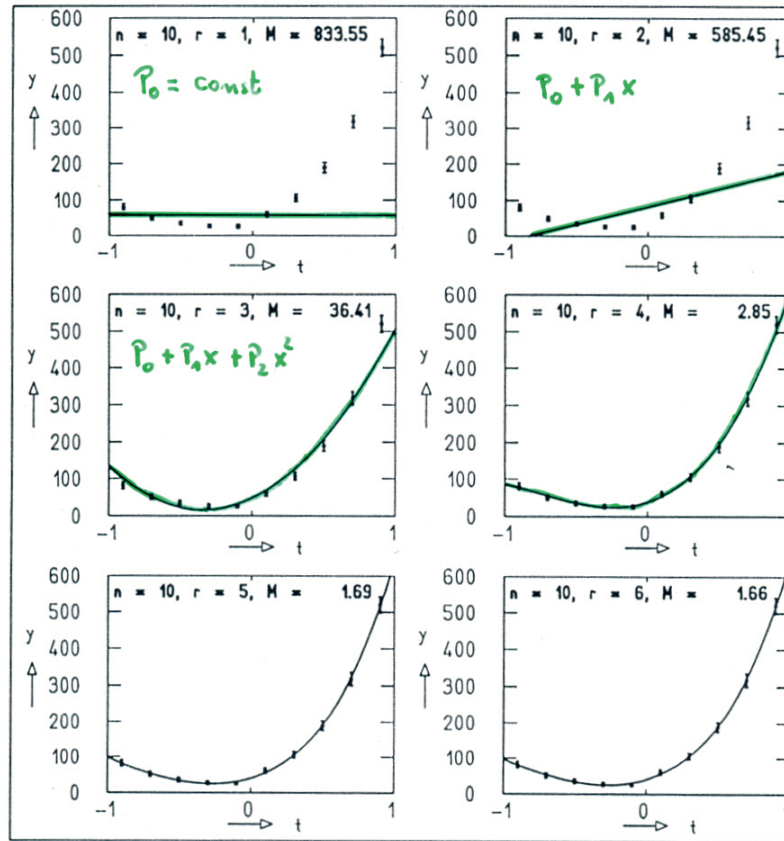
Beispiel: Polynom-Anpassung

$$y(x) = a_1 + a_2 \cdot x + a_3 \cdot x^2$$

$$H = \begin{pmatrix} 1 & x_1 & x_1^2 \\ 1 & x_2 & x_2^2 \\ \vdots & \vdots & \vdots \\ 1 & x_n & x_n^2 \end{pmatrix}$$

$$\vec{\lambda} = \begin{pmatrix} a_1 \\ a_2 \\ a_3 \end{pmatrix} = \begin{pmatrix} \sum 1 & \sum x_i & \sum x_i^2 \\ \sum x_i & \sum x_i^2 & \sum x_i^3 \\ \sum x_i^2 & \sum x_i^3 & \sum x_i^4 \end{pmatrix}^{-1} \begin{pmatrix} \sum y_i \\ \sum x_i \cdot y_i \\ \sum x_i^2 \cdot y_i \end{pmatrix}$$

Beispiel: Polynomapproximation an Messdaten



Fit-Parameter:

r	P_0	P_1	P_2	P_3	P_4	P_5	f	χ^2
1	57.85						9	833.55
2	82.66	99.10					8	585.45
3	47.27	185.96	273.61				7	36.41
4	37.94	126.55	312.02	137.59			6	2.85 ✓
5	39.62	119.10	276.49	151.91	52.60		5	1.68 ✓
6	39.88	121.39	273.19	136.58	56.90	16.72	4	1.66 ✓

↑
Parameter

↑
Freiheitsgrade

Komplizierterer, nicht-linearer Fall:

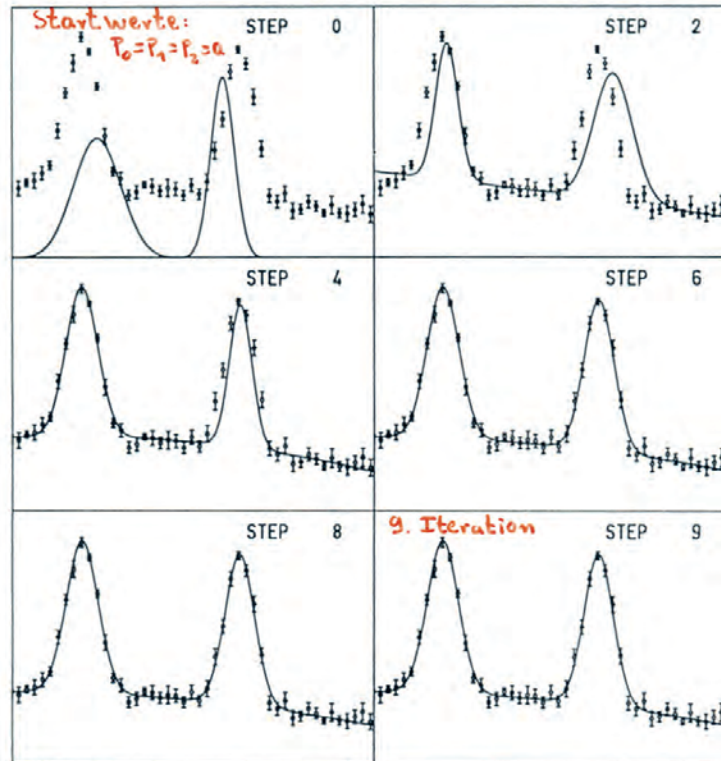


Bild 9.9: Schrittweise Annäherung der anzupassenden Funktion an die Meßwerte.

Zwei Signale : Gauß-Form

Untergrund : unbekannt, stetig → Polynom-Ansatz

$$f(x, \vec{\lambda}) = P_0 + P_1 \cdot x + P_2 \cdot x^2 + P_3 \cdot \exp\left\{-\frac{(P_4 - x)^2}{2 \cdot P_5^2}\right\} + P_6 \cdot \exp\left\{-\frac{(P_7 - x)^2}{2 \cdot P_8^2}\right\}$$

$$\vec{\lambda} = \begin{pmatrix} P_0 \\ P_1 \\ P_2 \\ \vdots \\ P_8 \end{pmatrix}$$

9 Parameter

→ benutze zuverlässige, erprobte Computer-Programme zur Minimum-Bestimmung.

z.B. **MINUIT** → Übung

Zusammenfassung Max. Likelihood Methode

Meßwerte: x_1, x_2, \dots, x_n

Wahrscheinlichkeitsdichte: $f(x, \vec{\lambda})$

Parameter: $\vec{\lambda} = (\lambda_1, \lambda_2, \dots, \lambda_m)$

Likelihood - Funktion: $\mathcal{L} = \prod_{i=1}^n f(x_i, \vec{\lambda})$

$$\ln \mathcal{L} = \sum_{i=1}^n \ln f(x_i, \vec{\lambda})$$

Max. Likelihood Schätzer $\hat{\lambda}$:
(globales Maximum der Likelihood Funktion)

$$\left. \frac{d \ln \mathcal{L}}{d \lambda_j} \right|_{\hat{\lambda}_j} = 0 \quad j=1, 2, \dots, m$$



Eigenschaften des Max. Likelihood Schätzers:

(i) konsistent: $\lim_{n \rightarrow \infty} \varepsilon^2(\hat{\lambda}) = 0.$

(ii) Invariant unter Parametertransformationen

$$\alpha \rightarrow \beta(\alpha)$$

$$\hat{\alpha} \rightarrow \hat{\beta}(\hat{\alpha})$$

Max. Likelihood Schätzer kann verzerrt sein:

$$E\{\hat{\lambda}\} = \int \hat{\lambda} \cdot \mathcal{L} \cdot dX = \lambda_0 (1 + \varepsilon(n))$$

$$\varepsilon(n) \rightarrow 0 \quad n \rightarrow \infty.$$

(iii) Für $n \rightarrow \infty$ ist die max. Likelihood Schätzung effizient, d.h. die Varianz nimmt den kleinstmöglichen Wert an

$$\text{Var}(\hat{\lambda}) = - \frac{1}{E \left\{ \frac{d^2 \ln \mathcal{L}}{d\lambda^2} \Big| \hat{\lambda} \right\}}$$

Cramér-Rao Bound.

II. Fehler der Parameter

Wenn $\frac{d^2 \ln \mathcal{L}}{d\lambda^2} = \text{const}$ (z.B. Gaußverteilung)

$$\Rightarrow \ln \mathcal{L} = - \frac{(\lambda - \hat{\lambda})^2}{2b^2} + c \quad \text{Parabel}$$

1- σ Variation: $\Delta \ln \mathcal{L} = 1/2$
 $\Delta \ln \mathcal{L} = n^2/2$

auch dann, wenn $\ln \mathcal{L}$ nicht parabolisch wird diese Definition beibehalten



mehrere Parameter:

Kovarianzmatrix der Parameter aus den zweiten Ableitungen

$$a_{ij} = - \frac{\partial^2 \ln \mathcal{L}}{\partial \lambda_i \partial \lambda_j} \Big|_{\hat{\lambda}}$$

$$\boxed{C = A^{-1}}$$

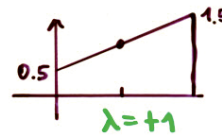
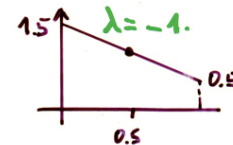
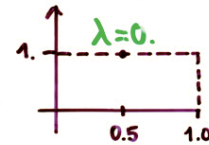
7.2. Beispiele

-3-

Beispiel:

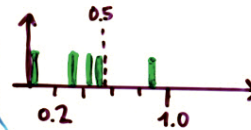
$$f(x; \lambda) = 1.0 + \lambda \cdot (x - 0.5)$$

$$\int_0^1 f(x, \lambda) \cdot dx = \underline{1.0}$$



ges. Parameter: λ

beobachtete Werte: 0.89, 0.03, 0.50, 0.36, 0.49



$$\lambda = +1.0 \quad \ln L = \ln 1.39 + \ln 0.53 + \underline{\ln 1.0} + \ln 0.86 + \ln 0.99 = -0.47$$

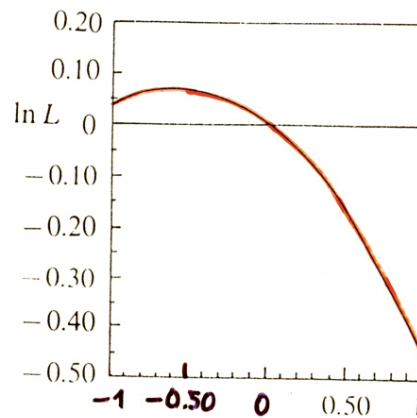
$$\lambda = -0.5 \quad \ln L = \ln 0.81 + \ln 1.24 + \underline{\ln 1.0} + \ln 1.07 + \ln 1.01 = 0.08$$

$$\lambda = -1.0 \quad \ln L = \ln 0.61 + \ln 1.47 + \underline{\ln 1.0} + \ln 1.14 + \ln 1.01 = 0.03$$

max. likelihood
für $\lambda = -0.60$

$$\hat{\lambda} = -0.60$$

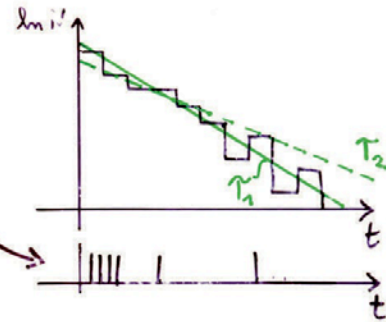
ML. - Schätzer



likelihood function.

Beispiel II: Lebensdauer eines Teilchens:

$$f(t, \tau) = \frac{1}{\tau} \cdot e^{-t/\tau}$$



n Meßwerte: t_1, t_2, \dots, t_n

gesuchter Parameter:
Lebensdauer τ .

$$\ln L = \sum_{i=1}^n \ln \left(\frac{1}{\tau} \cdot e^{-t_i/\tau} \right) = \sum_{i=1}^n \left(-\frac{t_i}{\tau} - \ln \tau \right)$$

$$\frac{d \ln L}{d \tau} = \sum_{i=1}^n \left(\frac{t_i}{\tau^2} - \frac{1}{\tau} \right)$$

Maximum: $\frac{d \ln L}{d \tau} \Big|_{\tau=\hat{\tau}} = 0 \iff \sum_{i=1}^n \left(\frac{t_i}{\hat{\tau}^2} - \frac{1}{\hat{\tau}} \right) = 0$

$$\rightarrow \sum_{i=1}^n \frac{t_i}{\hat{\tau}^2} = \frac{n}{\hat{\tau}}$$

$$\rightarrow \hat{\tau} = \frac{1}{n} \sum_{i=1}^n t_i$$

Bemerkungen:

- Exp. Effekte, wie z.B. Auflösungsfunktion, können elegant mitberücksichtigt werden \leftrightarrow Faltung

$$f(t, \tau) \rightarrow f(t, \tau, z) = f(t, \tau) \otimes G(z)$$

Gauß-Funktion

- jedes Ereignis wird individuell berücksichtigt, kein Binning

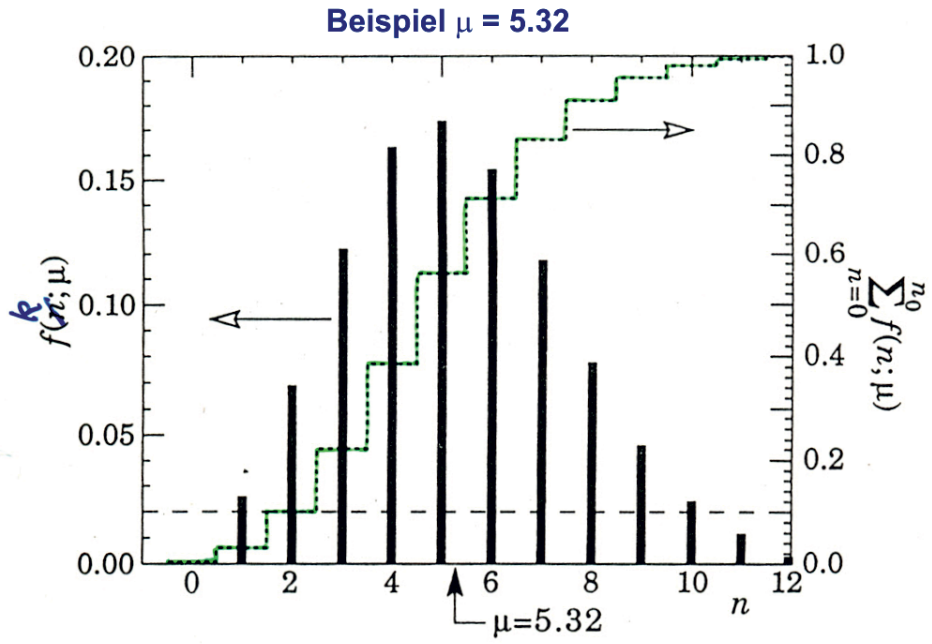


Table 17.3: Poisson upper limits N for n_0 observed events.

<i>Key</i> n_0	$\epsilon =$	$\epsilon =$	n_0	$\epsilon =$	$\epsilon =$
	10%	5%		10%	5%
0	2.30	<u>3.00</u>	6	10.53	11.84
1	3.89	4.74	7	11.77	13.15
2	<u>5.32</u>	6.30	8	13.00	14.44
3	6.68	7.75	9	14.21	15.71
4	7.99	9.15	10	15.41	16.96
5	9.27	10.51	11	16.60	18.21