### SMD-Abgabe

# 8. Übungsblatt

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22 23 24 <del>2</del> <del>5/6</del> <del>5/5</del> <del>16</del>,5/20 <del>5/6</del> <del>5/6</del>

Autopabe 23: a) Punkteder Geraden: (x1) und (x2)  $x^{3} = as^{3} + p$  =  $a = \frac{s^{3} - s^{4}}{x^{3} - x^{4}}$  $\Rightarrow b = x_1 - \frac{x_2 - x_1}{2_2 - 2_1} \cdot 2_1 + x_2 = \frac{2_1}{2_1 - 2_2} + x_2 = \frac{2_1}{2_1 - 2_2}$  $\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} z_1 & 1 \\ z_2 & 1 \end{pmatrix} \begin{pmatrix} q \\ q \end{pmatrix}$ (b) = 1 (1 -1) (x1) (V) Q/1 da die Geradlogleichung fehlt B = 30cobimatrix (V) Q/1 da die Geradlogleichung fehlt rechne V [9] = 1 (2-21)2 (-2, 21) (02 0) (1 -2) -0 BVB- Formel  $=\frac{1}{(z_{2}-z_{1})^{2}}\begin{pmatrix} O_{x_{1}}^{2} & -O_{x_{2}}^{2} \\ -O_{x_{1}}^{2}z_{2} & O_{x_{2}}^{2}z_{1} \end{pmatrix}\begin{pmatrix} 1 & -Z_{2} \\ -1 & Z_{1} \end{pmatrix}$  $= \frac{1}{(2x^{2}-21)^{2}} \left( \frac{O_{x_{1}}^{2} + O_{x_{2}}^{2}}{-(O_{x_{1}}^{2} + O_{x_{2}}^{2} + O_{x_{2}}^{2} + O_{x_{2}}^{2})} \right)$   $= \frac{1}{(2x^{2}-21)^{2}} \left( \frac{O_{x_{1}}^{2} + O_{x_{2}}^{2}}{-(O_{x_{1}}^{2} + O_{x_{2}}^{2} + O_{x_{2}}^{2} + O_{x_{2}}^{2})} \right)$   $= \frac{1}{(2x^{2}-21)^{2}} \left( \frac{O_{x_{1}}^{2} + O_{x_{2}}^{2}}{-(O_{x_{1}}^{2} + O_{x_{2}}^{2} + O_{x_{2}}^{2} + O_{x_{2}}^{2})} \right)$   $= \frac{1}{(2x^{2}-21)^{2}} \left( \frac{O_{x_{1}}^{2} + O_{x_{2}}^{2}}{-(O_{x_{1}}^{2} + O_{x_{2}}^{2} + O_{x_{2}}^{2} + O_{x_{2}}^{2})} \right)$   $= \frac{1}{(2x^{2}-21)^{2}} \left( \frac{O_{x_{1}}^{2} + O_{x_{2}}^{2}}{-(O_{x_{1}}^{2} + O_{x_{2}}^{2} + O_{x_{2}}^{2} + O_{x_{2}}^{2})} \right)$   $= \frac{1}{(2x^{2}-21)^{2}} \left( \frac{O_{x_{1}}^{2} + O_{x_{2}}^{2}}{-(O_{x_{1}}^{2} + O_{x_{2}}^{2} + O_{x_{2}}^{2} + O_{x_{2}}^{2})} \right)$   $= \frac{1}{(2x^{2}-21)^{2}} \left( \frac{O_{x_{1}}^{2} + O_{x_{2}}^{2} + O_{x_{2}}^{2} + O_{x_{2}}^{2}}}{-(O_{x_{1}}^{2} + O_{x_{2}}^{2} + O_{x_$  $p(a,b) = \frac{1}{C_{0}C_{0}} (ov(a,b)) = -\frac{(z_{0}C_{1}^{2} + z_{0}C_{2}^{2})}{((0x_{1}^{2} + 0x_{0}^{2} + 0x_{0}^{2} + 2x_{0}^{2})^{2}} \frac{(vorellations-1)}{(vorellations-1)} \frac{1}{(vorellations-1)} \frac{1}{(vor$ b)  $x_3 = a \cdot z_3 + b = \frac{z_2 - z_1}{z_3 - z_1} \cdot z_3 + x_1 - \frac{z_2 - z_1}{z_3 - z_1} \cdot z_1 + s_2 \cdot z_3$  $V[X_3] = \begin{pmatrix} \frac{1}{2} & \frac{1$ = (23-23 23-21) (-(0x1240x321) (0x123+0x321) 12-21) (23-21) (23-21) (23-21) = 123-211 [(0x+0x2)(22-23)2-(0x122+0x22)(23-21)] 1,5/2p 0x3 = [V[x] = (23-21)2 1 (0x1+0x2)(22-23)2-(0x122+0x221)(23-21)3 c) V [x3] = (2,-21)4 (2,-23 23-21) (0x1+0x3 0 0x123+0x321) (22-23) Noisillation = (53-51)4. [(02+03)(52-53)2+(0353+0253)(53-51)3] Ox30me = (22-21)2 1(02+02)(22-23)2+(02,22+022)(23-21)(23-21)2 (W) FF mit Korrellation fell => 0,5/1P. 54/6P. oty = \ 322 + 062 + 2(+3.00 (215))

## Aufgabe 22

a)

Gegeben:

$$y = a_o + a_1 \cdot x$$

$$a_0 = 1, 0 \pm 0, 2$$

$$a_1 = 1, 0 \pm 0, 2$$

$$\rho = -0, 8$$

Ohne Korrelation:

$$\sigma_y^2 = \left(\frac{\partial y}{\partial a_0}\sigma_{a_0}\right)^2 + \left(\frac{\partial y}{\partial a_1}\sigma_{a_1}\right)^2$$
$$= \sigma_{a_0}^2 + \sigma_{a_1}^2 x^2 = 0,04+0,04 \cdot x^2$$

Mit Korrelation:

$$\sigma_{y}^{2} = \left(\frac{\partial y}{\partial a_{0}}\sigma_{a_{0}}\right)^{2} + \left(\frac{\partial y}{\partial a_{1}}\sigma_{a_{1}}\right)^{2} + 2\frac{\partial y}{\partial a_{0}}\frac{\partial y}{\partial a_{1}} \cdot \sigma_{a_{0}}\sigma_{a_{1}} \cdot \rho$$

$$= \sigma_{a_{0}}^{2} + \sigma_{a_{1}}^{2}x^{2} + 2 \cdot \sigma_{a_{0}}\sigma_{a_{1}} \cdot \rho x$$

$$= 0,04 \cdot x^{2} - 0,064 \cdot x + 0,04$$

b)

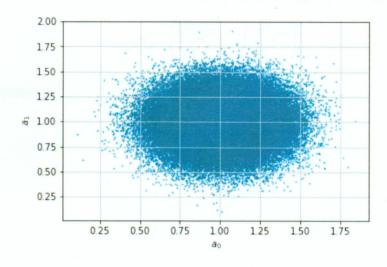
```
In [33]: import numpy as np
   import uncertainties as unc
   import uncertainties.unumpy as unp
   from uncertainties import correlated_values
   from scipy.optimize import curve_fit
   import matplotlib.pyplot as plt
   np.random.seed(42)
```

```
In [34]: def parabel(x, a, b, c):
    return a*x**2+b*x+c
```

#### Ohne Korrelation

#### **Scatterplot**

```
In [36]: Zufall=np.random.multivariate_normal(mean = [a_0.n, a_1.n], cov = co
    vmatrix, size=10**5) # Einzig hübsche Funktion die ich gefunden habe
    , die Zufallszahlen mit Mittelwert und Standard-Abweichungen generie
    rt
    a0_ok=Zufall[:,0]
    a1_ok=Zufall[:,1]
    plt.scatter(a0_ok, a1_ok, s=0.5)
    plt.xlabel(r'$a_0$')
    plt.ylabel(r'$a_1$')
    plt.grid()
    print(a_0.n, np.mean(a_0))
    print(a_1.n, np.mean(a_1))
```





#### **Numerische Berechnung**

1.0 1.00+/-0.20

```
In [37]: xx = np.linspace(-10, 10, 100)
    array=[]
    for x in xx:
        y=a0_ok+a1_ok*x
        yy = np.var(y)
        array.append(yy)

params, cov0 = curve_fit(parabel, xx, array)
    a, b, c = params
    print(params)
    print(a, b, c)

[0.03984436 0.00016159 0.04014075]
    0.03984436065601598 0.00016159282630883538 0.04014074532424168
```

 $f(x) = ax^2 + bx + c = 0.0398x^2 + 0.0002x + 0,0401$ 

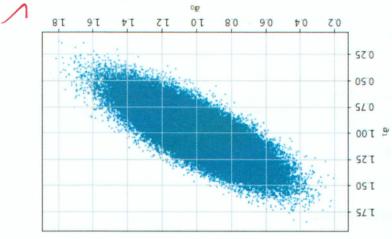


#### Mit Korrelation

1

#### Scatterplot

```
()birg.Jlq
                                                 plt.ylabel(r'$a_l$')
                                                 plt.xlabel(r'$a_0$')
                                     plt.scatter(a0_mk, al_mk, s=0.5)
                                                    al_mk=Zufall[:,1]
                                                    a0_mk=Zufall[:,0]
, die Zufallszahlen mit Mittelwert und Standard-Abweichungen generie
vmatrix, size=10**5) # Einzig hübsche Funktion die ich gefunden habe
In [39]; Zufall=np.random.multivariate_normal(mean = [a_0.n, a_l.n], cov = co
```



#### Numerische Berechnung

```
print (params)
                                  g' p' c = bgrams
params, cov0 = curve_fit(parabel, xxx, array2)
                            array2.append(yy)
                     yy = np.var(y, ddof = 1)
                               \lambda = 30 \text{ mk} + 31 \text{ mk*x}
                                      :xxx ui x rol
                                          array2=[]
                    In [40]: | xxx = np.linspace(0, 5, 100)
```

return sigma\_a0\*\*2+sigma\_a1\*\*2\*x\*\*2 + 2\*cov\*x

def varianz mk(x, sigma\_a0, sigma\_a1, cov):

return sigma\_a0\*\*2 + Sigma\_a1\*\*2\*x\*\*2

[74821040.0 72820440.0-44296980.0]

 $10 \neq 0$ ,  $0 + x \neq 0$ , 0 - 2x = 0,  $0 \neq 0 \neq 0$ 

In [41]: def varianz ok(x, sigma a0, sigma al):

(၁

#### Unkorreliert

```
In [42]: xx=\{-3, 0, 3\}
         for x in xx:
             print('x =',x,':')
             meanAn = 1+x
             stdAn = np.sqrt(varianz ok(x, 0.2, 0.2))
            y = a0 \text{ ok+a1 ok*x}
            meanMC = np.mean(y)
             stdMC = np.std(y)
             print('Analytischer Mittelwert =', meanAn, ', Standardabweichung
             print('Monte-Carlo Mittelwert =', meanMC,', Standardabweichung =
         ', stdMC)
             print('Abweichung des Mittelwerts =', (meanMC-meanAn)/meanAn*100
         , 181)
             print('Abweichung =', (stdMC-stdAn)/stdAn*100, '% \n')
         Analytischer Mittelwert = 1 , Standardabweichung = 0.2
         Monte-Carlo Mittelwert = 1.0011420114028204 , Standardabweichung =
         0.200351554334479
         Abweichung des Mittelwerts = 0.1142011402820442 %
         Abweichung = 0.1757771672394881 %
         x = 3:
         Analytischer Mittelwert = 4 , Standardabweichung = 0.6324555320336
         Monte-Carlo Mittelwert = 3.9988847185005585 , Standardabweichung =
         0.6318423614378131
         Abweichung des Mittelwerts = -0.027882037486037792 %
         Abweichung = -0.09695078385846202 %
         Analytischer Mittelwert = -2 , Standardabweichung = 0.632455532033
         Monte-Carlo\ Mittelwert = -1.9966006956949185, Standardabweichung
         = 0.6310746491101183
         Abweichung des Mittelwerts = -0.16996521525407537 %
         Abweichung = -0.21833676102371732 %
                                          Schön, aber nur korte liert
```

Korreliert

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```
In [13]: xx=\{-3, 0, 3\}
         for x in xx:
            print('x = ',x,!:')
            meanAn = 1+x
            stdAn = np.sqrt(varianz mk(x, 0.2, 0.2, -0.032))
            y = a0 mk+a1 mk*x
             meanMC = np.mean(y)
             stdMC = np.std(y)
            print('Analytischer Mittelwert =', meanAn, ', Standardabweichung
         =', stdAn)
            print('Monte-Carlo Mittelwert =', meanMC,', Standardabweichung =
         ', stdMC)
            print('Abweichung des Mittelwerts =', (meanMC-meanAn)/meanAn*100
           181)
             print('Abweichung=', (stdMC-stdAn)/stdAn*100, '% \n')
         x = 0:
         Analytischer Mittelwert = 1 \square Standardabweichung = 0.2
         Monte-Carlo Mittelwert = 1.0002855463340872 , Standardabweichung =
         0.2003074389650816
         Abweichung des Mittelwerts = 0.028554633408717223 %
         Abweichung= 0.1537194825407956 %
         x = 3:
         Analytischer Mittelwert = 4 , Standardabweichung = 0.4560701700396
         Monte-Carlo Mittelwert = 3.999391221542233 , Standardabweichung =
         0.4556507003969493
         Abweichung des Mittelwerts = -0.015219461444171412 %
         Abweichung= -0.091974803497789 %
         x = -3:
         Analytischer Mittelwert = -2 Standardabweichung = 0.769415362466
         8538
         Monte-Carlo Mittelwert = -1.9988201288740588 , Standardabweichung
         = 0.7693798578621581
         Abweichung des Mittelwerts = -0.058993556297060046 %
         Abweichung= -0.004614491265403017 %
```

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## Aufgabe 24

a)

Designmatrix aufstellen:

$$A = \begin{pmatrix} \cos\left(\frac{6}{6}\pi\right) & \sin\left(\frac{0}{6}\pi\right) \\ \cos\left(\frac{1}{6}\pi\right) & \sin\left(\frac{1}{6}\pi\right) \\ \cos\left(\frac{2}{6}\pi\right) & \sin\left(\frac{2}{6}\pi\right) \\ \cos\left(\frac{3}{6}\pi\right) & \sin\left(\frac{3}{6}\pi\right) \\ \cos\left(\frac{4}{6}\pi\right) & \sin\left(\frac{4}{6}\pi\right) \\ \cos\left(\frac{5}{6}\pi\right) & \sin\left(\frac{5}{6}\pi\right) \\ \cos\left(\frac{6}{6}\pi\right) & \sin\left(\frac{6}{6}\pi\right) \\ \cos\left(\frac{7}{6}\pi\right) & \sin\left(\frac{7}{6}\pi\right) \\ \cos\left(\frac{8}{6}\pi\right) & \sin\left(\frac{8}{6}\pi\right) \\ \cos\left(\frac{9}{6}\pi\right) & \sin\left(\frac{9}{6}\pi\right) \\ \cos\left(\frac{10}{6}\pi\right) & \sin\left(\frac{10}{6}\pi\right) \\ \cos\left(\frac{11}{6}\pi\right) & \sin\left(\frac{11}{6}\pi\right) \end{pmatrix}$$

bei der Aufgabe ist kein python nöbj, auch per Hand import numpy as np rechenbar, is being für klauser... b) In [2]: import numpy as np

 $\hat{a} = \left(A^T A\right)^{-1} A^T y$ 

```
In [3]: A=np.matrix([[np.cos(0), np.sin(0)],
                        [np.cos(1/6*np.pi), np.sin(1/6*np.pi)],
                        [np.cos(2/6*np.pi), np.sin(2/6*np.pi)],
                        [np.cos(3/6*np.pi), np.sin(3/6*np.pi)],
                         [np.cos(4/6*np.pi), np.sin(5/6*np.pi)],
                        [np.cos(5/6*np.pi), np.sin(5/6*np.pi)],
                         [np.cos(6/6*np.pi), np.sin(6/6*np.pi)],
                         [np.cos(7/6*np.pi), np.sin(7/6*np.pi)],
                         [np.cos(8/6*np.pi), np.sin(8/6*np.pi)],
                         [np.cos(9/6*np.pi), np.sin(9/6*np.pi)],
                         [np.cos(10/6*np.pi), np.sin(10/6*np.pi)],
                         [np.cos(11/6*np.pi), np.sin(11/6*np.pi)]])
          y=np.matrix([-0.032, (.01), (0.05), 0.068, 0.076, 0.080, 0.031, 0.005, -0.041, .041 -0.090, -0.088, -0.074])

hiv kin Forma descript wine Dimension probleme

a=(A.T*A)**(-1)*A.T*y.T
```

Out[3]: matrix([[-0.04019568],

$$a_0 = -0.0401956$$
 $a_1 = 0.08817037$ 

C)

 $V[\hat{a}] = \sigma^2 \left(A^T A\right)^{\frac{1}{2}}$ 

In [4]: sigma = 0.011 V = sigma\*\*2 \* (A.T \* A) (1)

Out[4]: matrix([[ 2.01871558e-05, -6.71728350e-07], [-6.71728350e-07, 2.20223518e-05]])

In [5]: np.sqrt(V[0,0]), np.sqrt(V[1,1])

Out[5]: (0.004493011885516234, 0.004692797863270538)

Also ergibt sich:

$$\sigma_{lpha_1} = 4,49 \cdot 10^{-3} \ \sigma_{lpha_2} = 4,69 \cdot 10^{-3} \ 
angle$$

In [6]: rho=V[0, 1]/(np.sqrt(V[0,0]\*V[1, 1]))
rho

Out[6]: -0.0318584221555165

womit

$$\rho = \frac{\text{Cov}(\alpha_{\text{N}} \alpha_{\text{I}})}{\sigma_{\text{I}} \alpha_{\text{I}} \sigma_{\text{I}}} = \frac{-6,717 \cdot 10^{-7}}{\sqrt{2,019 \cdot 10^{-5} \cdot 2,202 \cdot 10^{-5}}} = -0,032$$
Sollte mit sichtige Water noch kleiner Sein pa o

folgt.

d)

Es gilt:

 $\cos \left(\Psi + \delta
ight) = \cos \left(\Psi
ight) \cos \left(\delta
ight) - \sin \left(\Psi
ight) \sin \left(\delta
ight)$ 

Daraus folgt:

 $a_1 = A_0 \cdot \cos \delta$   $a_2 = -A_0 \cdot \sin \delta$ 

und daraus wiederum

$$a_1^2 + a_2^2 = A_0^2 \to A_0 = \sqrt{a_1^2 + a_2^2} V$$
 $\delta = -\arctan \frac{a_2}{a_1} = S = a_1 c \tan \left(-\frac{a_2}{a_1}\right)$ 

n 3

Für die Fehler folgt dann:

$$\sigma_{A_0} = \sqrt{rac{a_0^2}{a_1^2 + a_0^2} \sigma_{a_0}^2 + rac{a_1^2}{a_1^2 + a_0^2} \sigma_{a_1}^2 + 2rac{a_0a_1}{(a_1^2 + a_0^2)} \cdot ext{Cov}(a_0, a_1)} pprox 0,0045$$
 $\sigma_{\delta} = \sqrt{rac{a_0^2}{(a_1^2 + a_0^2)^2} \sigma_{a_0}^2 + rac{a_1^2}{(a_1^2 + a_0^2)^2} \sigma_{a_1}^2 - 2rac{a_0a_1}{(a_1^2 + a_0^2)^2} \cdot ext{Cov}(a_0, a_1)} pprox 0,05$ 

$$A_0 = 0,0958 \pm 0,0045$$
 ( )  $\delta = 1.1450 \pm 0,0467$  ( )

Kovarian & mattix mit BVBT Formel aus rechnen, dann kann auch die Korrelation berechnet werden

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