StatsKurs_Uebung_Tag4

November 18, 2019

1 Einführung in die Statistik mit Python - Tag 4

1.1 Korrelation

1.1.1 Pearson-Produkt Moment Korrelation

```
In [1]: import math

        def correlation(x, y):
          n = len(x)

          # Mittelwerte berechnen
          x_mn = sum(x) / n
          y_mn = sum(y) / n

          # Varianzen berechnen
          var_x = (1 / (n-1)) * sum(map(lambda xi: (xi - x_mn) ** 2 , x))
          var_y = (1 / (n-1)) * sum(map(lambda yi: (yi - y_mn) ** 2 , y))

          # Standardabweichungen berechenen
          std_x, std_y = math.sqrt(var_x), math.sqrt(var_y)

          # Kovarianz berechnen
          xy_var = map(lambda xi, yi: (xi - x_mn) * (yi - y_mn), x, y)
          cov = (1 / (n-1)) * sum(xy_var)

          # Korrelationskoeffizient nach Pearson
          r = cov / (std_x * std_y)
          return float(f"{r:.3f}")

        # Wohnungsgröe in Quadratmetern, Mietkosten
        sqrm = [20, 30, 40, 50, 60]
        cost = [300, 400, 600, 700, 1000]

        print(correlation(sqrm, cost)) #out: 0.981
```

```
0.981
```

In [2]:
```python
import pandas as pd

df = pd.DataFrame({"sqrm": sqrm, "cost": cost})
df.corr()
```

Out[2]:

	sqrm	cost
sqrm	1.000000	0.981495
cost	0.981495	1.000000

In [3]:
```python
import numpy
numpy.corrcoef(sqrm, cost)[0, 1]
```

Out[3]: 0.9814954576223638

In [4]:
```python
from scipy.stats.stats import pearsonr
import numpy as np

# another way to access the help of a certain function
# from pydoc import help
# help(pearsonr)

print(pearsonr(sqrm, cost))
```

```
(0.9814954576223638, 0.0030132990718159991)
```

1.1.2 Spearman Rank Korrelation

In [5]:
```python
from collections import Counter

def ranking(array):
  counts = Counter(array)
  array_sorted = sorted(set(array))
  rank = 1
  rankings = {}
  for num in array_sorted:
    count = counts.get(num)
    if count == 1:
      rankings[num] = rank
      rank += 1
    else:
      rankings[num] = sum(range(rank, rank+count)) / count
      rank += count
  return [float(rankings.get(num)) for num in array]

# Beispiel für eine Rangkorrelation
eng = [12, 12, 3, 6, 10, 4, 15, 8]
deu = [14, 14, 5, 4, 11, 8, 10, 3]
```

```
eng_rank = ranking(eng) # [6.5, 6.5, 1.0, 3.0, 5.0, 2.0, 8.0, 4.0]
deu_rank = ranking(deu) # [7.5, 7.5, 3.0, 2.0, 6.0, 4.0, 5.0, 1.0]

correlation(eng_rank, deu_rank) #out: 0.639
```

Out[5]: 0.639

```
In [6]: ### Spearmans Correlations
        import scipy.stats as stats
        print(stats.spearmanr(eng,deu))
```

```
SpearmanrResult(correlation=0.6385542168674698, pvalue=0.08836256884491352)
```

1.2 Lineare Regression

```
In [7]: ## First, we generate simulated data according to the model:
        import pandas as pd
        import numpy as np
        x = np.linspace(-5, 5, 20)
        np.random.seed(1)

        # normal distributed noise
        y = -5 + 3*x + 4 * np.random.normal(size=x.shape)

        # Create a data frame containing all the relevant variables
        data = pd.DataFrame({'x': x, 'y': y})

        ## Then we specify an OLS model and fit it:

        from statsmodels.formula.api import ols
        model = ols("y ~ x", data).fit()

        ## We can inspect the various statistics derived from the fit:

        print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.804
Model:                            OLS   Adj. R-squared:                  0.794
Method:                 Least Squares   F-statistic:                     74.03
Date:                Mon, 18 Nov 2019   Prob (F-statistic):           8.56e-08
Time:                        14:04:12   Log-Likelihood:                -57.988
No. Observations:                  20   AIC:                             120.0
Df Residuals:                      18   BIC:                             122.0
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
```

```
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     -5.5335      1.036     -5.342      0.000      -7.710      -3.357
x              2.9369      0.341      8.604      0.000       2.220       3.654
==============================================================================
Omnibus:                        0.100   Durbin-Watson:                   2.956
Prob(Omnibus):                  0.951   Jarque-Bera (JB):                0.322
Skew:                          -0.058   Prob(JB):                        0.851
Kurtosis:                       2.390   Cond. No.                         3.03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

1.2.1 Quadratic Polynomial

In [8]:
```python
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import statsmodels.formula.api as smf

''' Generate a noisy, slightly quadratic dataset '''
x = np.arange(100)
y = 150 + 3*x + 0.03*x**2 + 5*np.random.randn(len(x))

# Turn the data into a pandas DataFrame, so that we
# can address them in the formulas with their name
df = pd.DataFrame({'x':x, 'y':y})

# Fit the models, and show the results
Res1 = smf.ols('y~x', df).fit()
Res2 = smf.ols('y ~ x+I(x**2)', df).fit()
Res3 = smf.ols('y ~ x+I(x**2)+I(x**3)', df).fit()
```

1.2.2 Modellkoeffizienten

In [9]:
```python
print('The coefficients from the linear fit: {0}'.format(Res1.params))
print('The coefficients from the quadratic fit: {0}'.format(Res2.params))
print('The coefficients from the cubic fit: {0}'.format(Res3.params))
```

```
The coefficients from the linear fit: Intercept    102.078323
x              5.965156
dtype: float64
The coefficients from the quadratic fit: Intercept    149.285603
x              3.074914
I(x ** 2)      0.029194
dtype: float64
```

```
The coefficients from the cubic fit: Intercept    149.387903
x              3.062193
I(x ** 2)      0.029517
I(x ** 3)     -0.000002
dtype: float64
```

1.2.3 Konfidenzintervall

```
In [10]: Res1.conf_int()
         # The confidence intervals are of particular interest, as parameters whose
         # confidence intervals overlap zero are not significant.
```

```
Out[10]:                   0           1
         Intercept  93.27071  110.885936
         x           5.81145    6.118861
```

1.2.4 Finde das Model mit dem "best-fit"

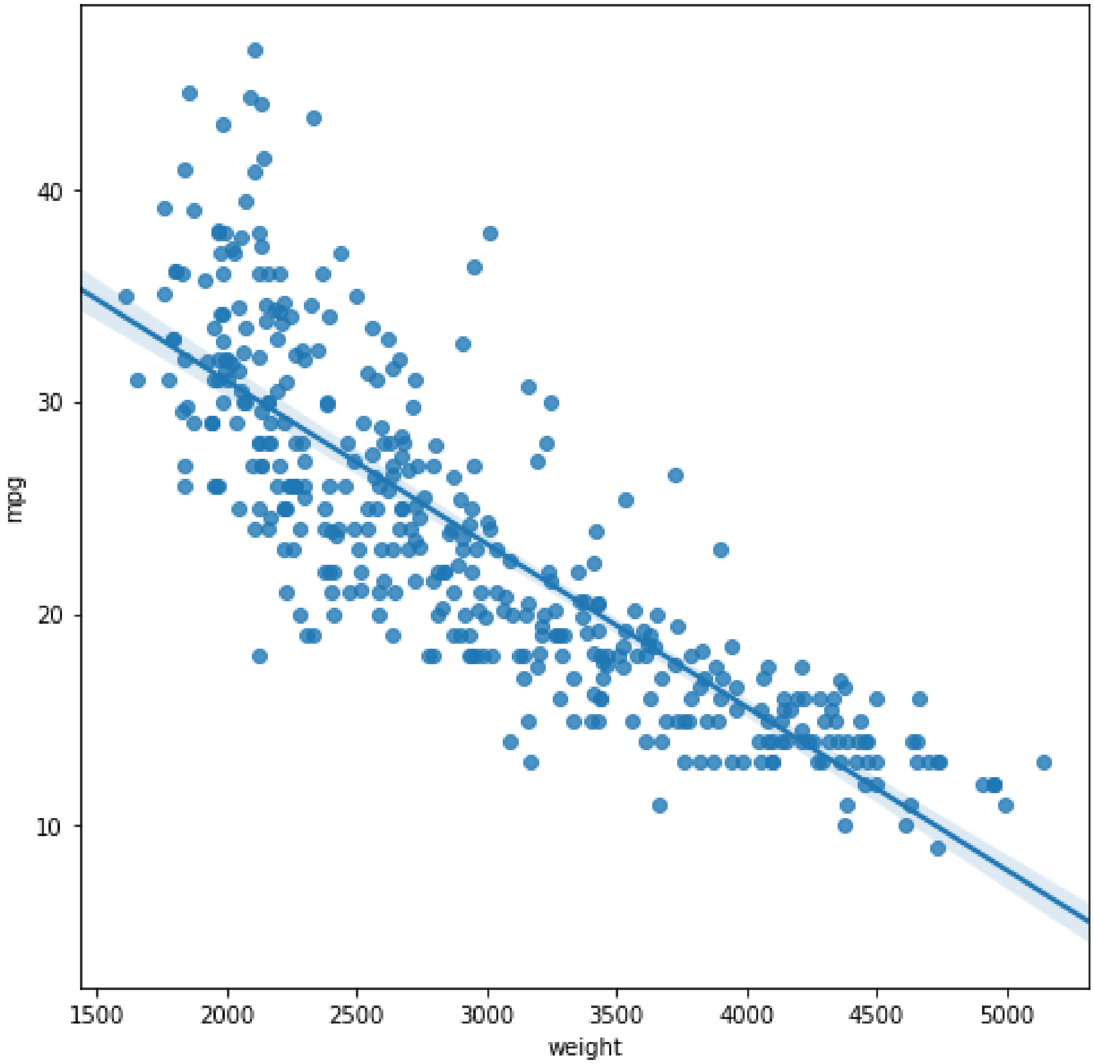
```
In [11]: '''Solution with the tools from statsmodels'''
         import statsmodels.api as sm

         # Extract the AIC of all three Models
         print("""The AIC-value is {0:4.1f} for the linear fit,\n
               {1:4.1f} for the quadratic fit, and \n
               {2:4.1f} for the cubic fit""".format(Res1.aic, Res2.aic, Res3.aic))
```

```
The AIC-value is 907.2 for the linear fit,

      570.8 for the quadratic fit, and

      572.8 for the cubic fit
```

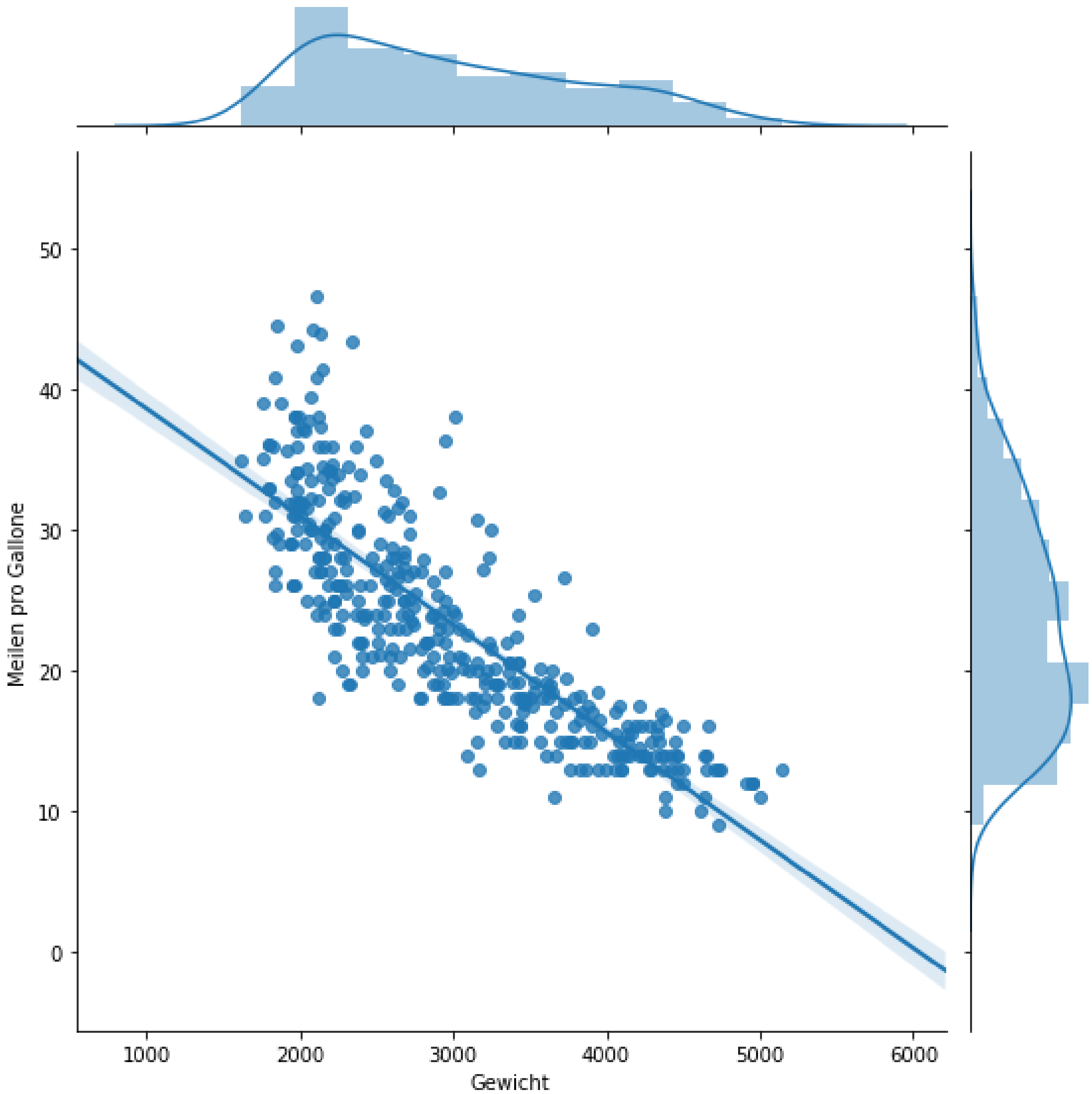
1.2.5 Zusammenhänge mit Regplot und Jointplot darstellen

```
In [12]: import seaborn as sns
         import matplotlib.pyplot as plt

         # Datensatz
         cars = sns.load_dataset("mpg")

         # Figure und Axes Objekt anlegen
         fig, ax = plt.subplots(figsize=(8, 8))

         # Grafik anlegen
         conf = {"x": "weight", "y": "mpg",
                 "data": cars, "ax": ax}
         sns.regplot(**conf)
```

```
# Grafik anzeigen
plt.show()
```




```
In [13]: conf = {"x": "weight", "y": "mpg",
                 "kind": "reg", "data": cars,
                 "height": 8, "ratio": 6}
         f = sns.jointplot(**conf)
         f.set_axis_labels("Gewicht",
                           "Meilen pro Gallone")

         # Grafik anzeigen
         plt.show()
```



1.3 Übung

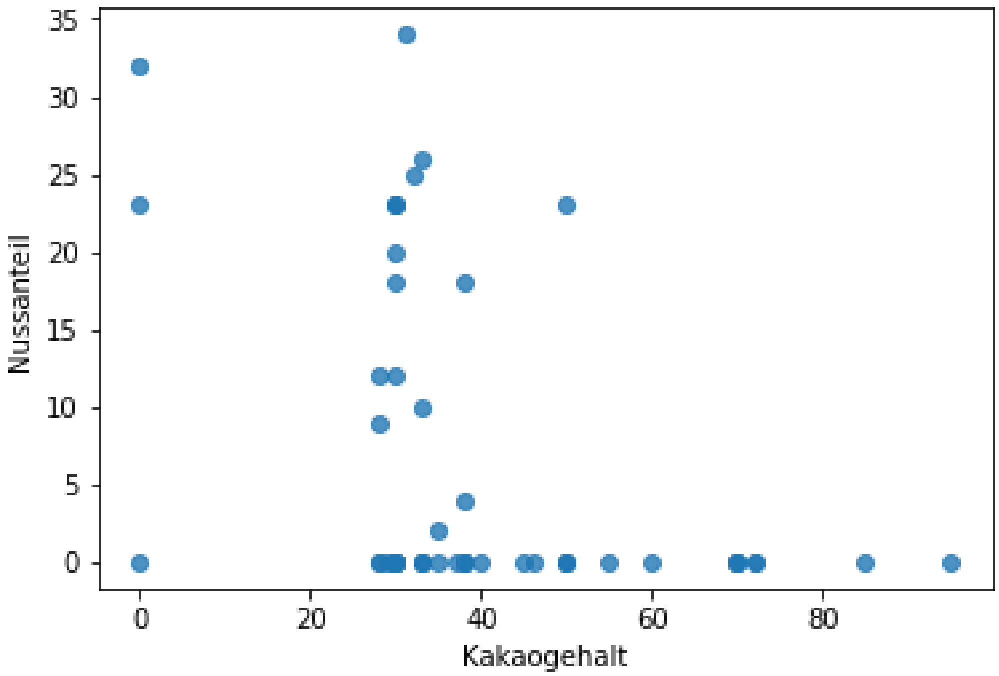
Lade den Datensatz **schoko.csv** in Python

```
In [14]: import pandas as pd
         schoko = pd.read_csv("/home/matt/Documents/Github/pyStats/data/schoko.csv")
```

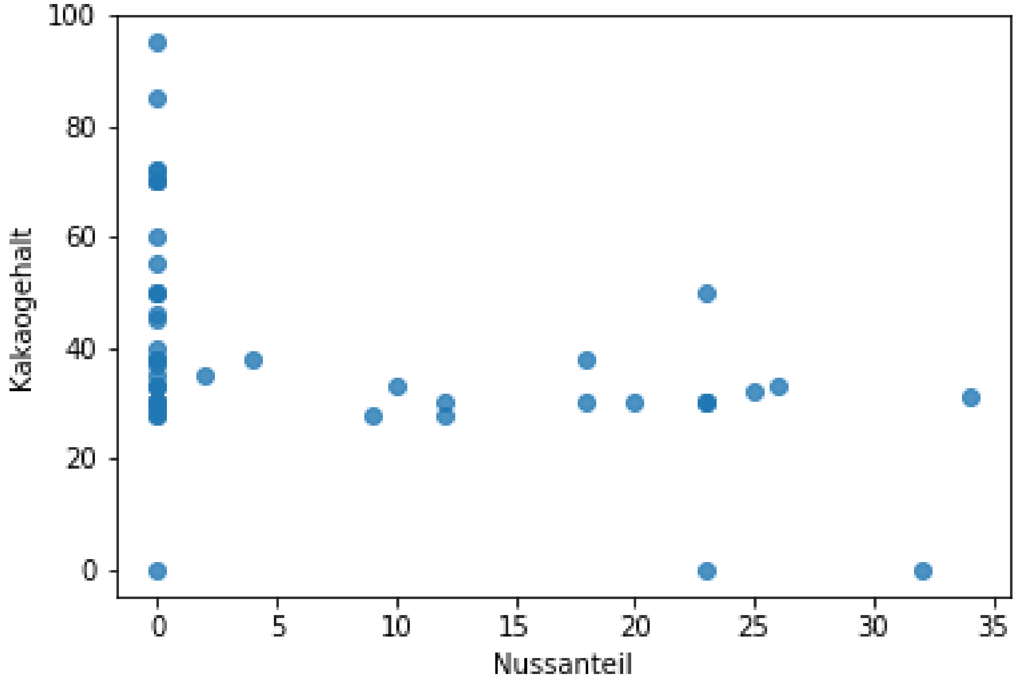
Erstelle eine Korrelation zwischen Kakaogehalt und Nussanteil (visuell und statistisch)

```
In [15]: # library & dataset
         import seaborn as sns
         import matplotlib.pyplot as plt
```

```python
# use the function regplot to make a scatterplot
sns.regplot(x=schoko["Kakaogehalt"], y=schoko["Nussanteil"], fit_reg=False)
plt.show()

sns.regplot(x=schoko["Nussanteil"], y=schoko["Kakaogehalt"], fit_reg=False)
```

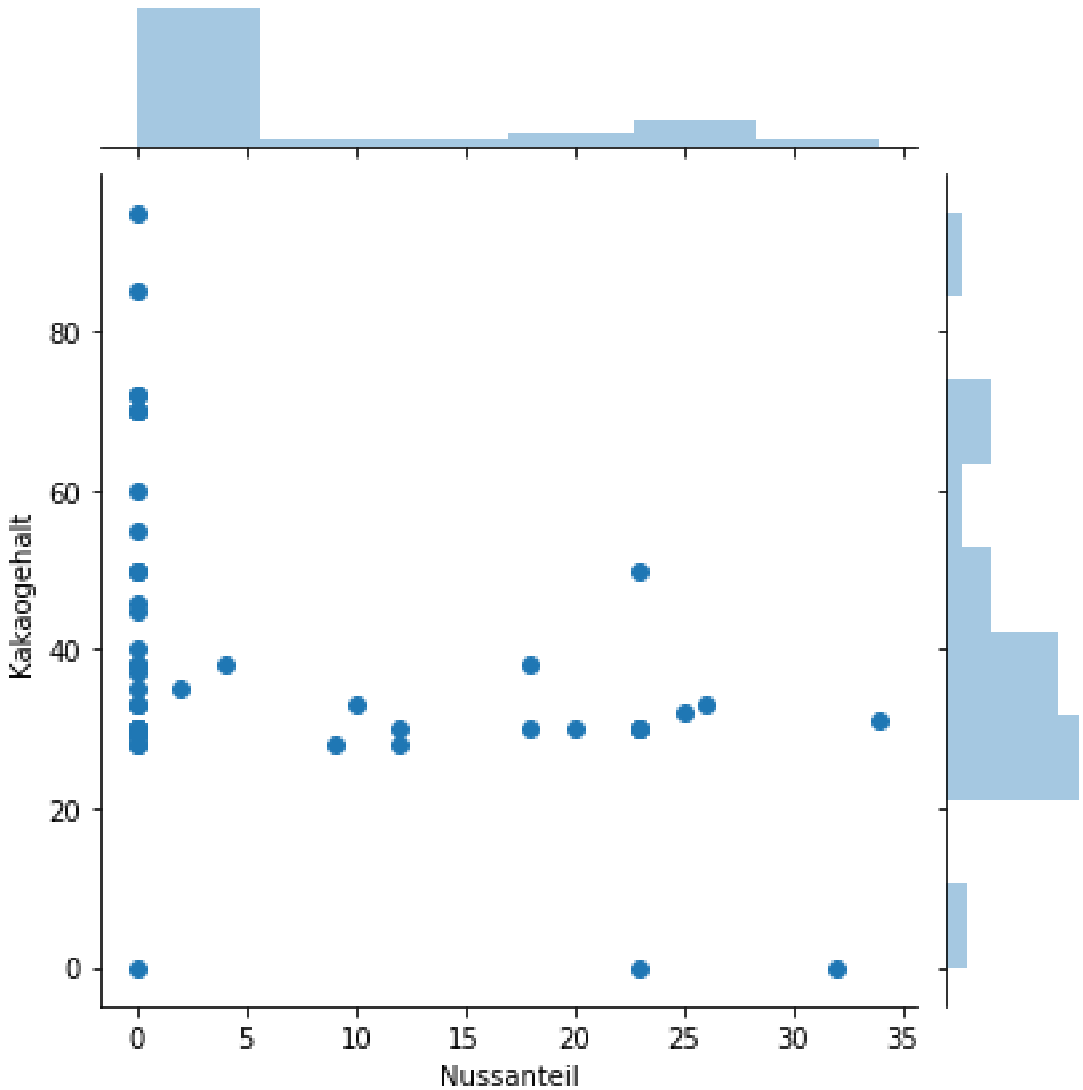



```
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1fc0e12dd8>
```




```
In [16]: sns.jointplot(x=schoko["Nussanteil"], y=schoko["Kakaogehalt"])
```

```
Out[16]: <seaborn.axisgrid.JointGrid at 0x7f1fc0d74668>
```



In [17]:
```
import scipy.stats as stats

stats.spearmanr(schoko["Nussanteil"], schoko["Kakaogehalt"], nan_policy="omit")
```

Out[17]: SpearmanrResult(correlation=-0.40319136452035337, pvalue=0.0030396203105086104)

In [18]:
```
# Ohne drop NA
correlation(ranking(list(schoko["Nussanteil"])), ranking(list(schoko["Kakaogehalt"]))

###
# Nicht sinnvoll!!!
###
```

Out[18]: -0.439

```
In [19]: #Oder

         # Need to run Sektion 1 & 5 to get Correlation & Ranking function

         # Remove NAs
         schoko_sub = schoko.dropna(subset=['Nussanteil', 'Kakaogehalt'])
         #?schoko.dropna

         # Run correlation
         correlation(ranking(list(schoko_sub["Nussanteil"])), ranking(list(schoko_sub["Kakaoge
```

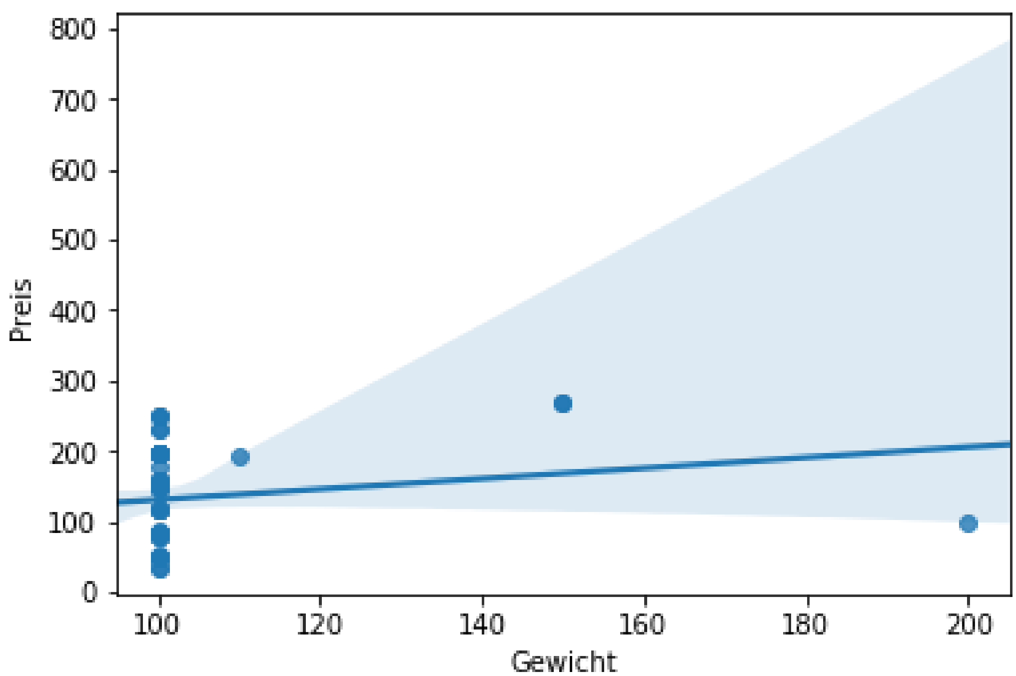
```
Out[19]: -0.403
```

```
In [20]: stats.pearsonr(schoko["Nussanteil"], schoko["Kakaogehalt"])
         #?stats.pearsonr
```

```
Out[20]: (nan, 1.0)
```

Erklärt das Gewicht der Schokolade den Preis? Prüfe dies visuell und statistisch

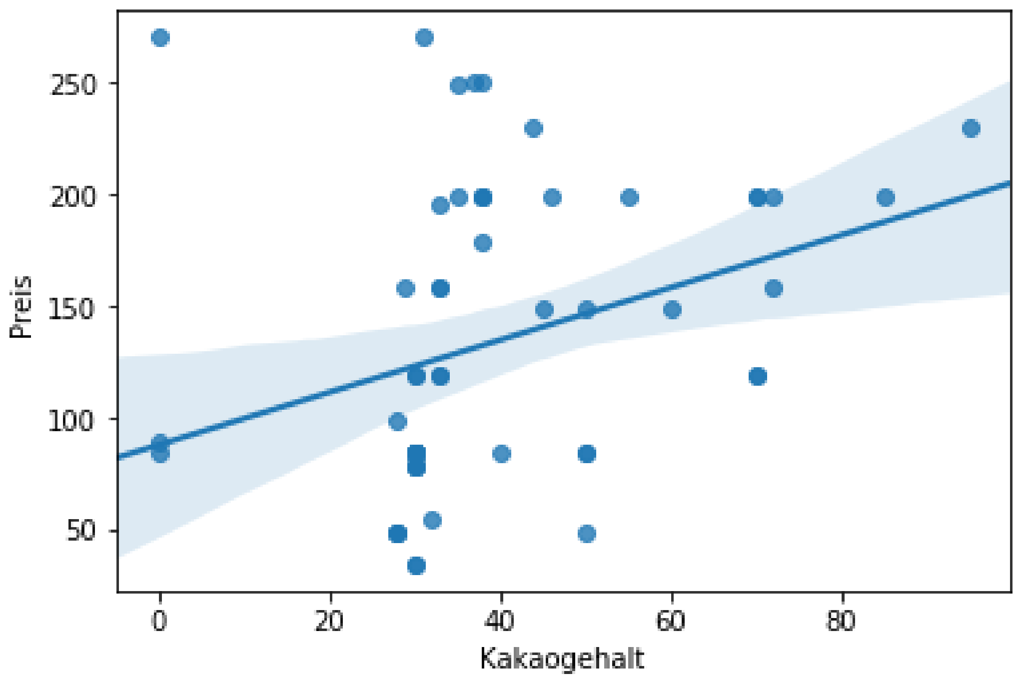
```
In [21]: # use the function regplot to make a scatterplot
         sns.regplot(x=schoko["Gewicht"], y=schoko["Preis"], fit_reg=True)
         plt.show()
```



Erklärt der Kakaogehalt den Preis der Schokolade?

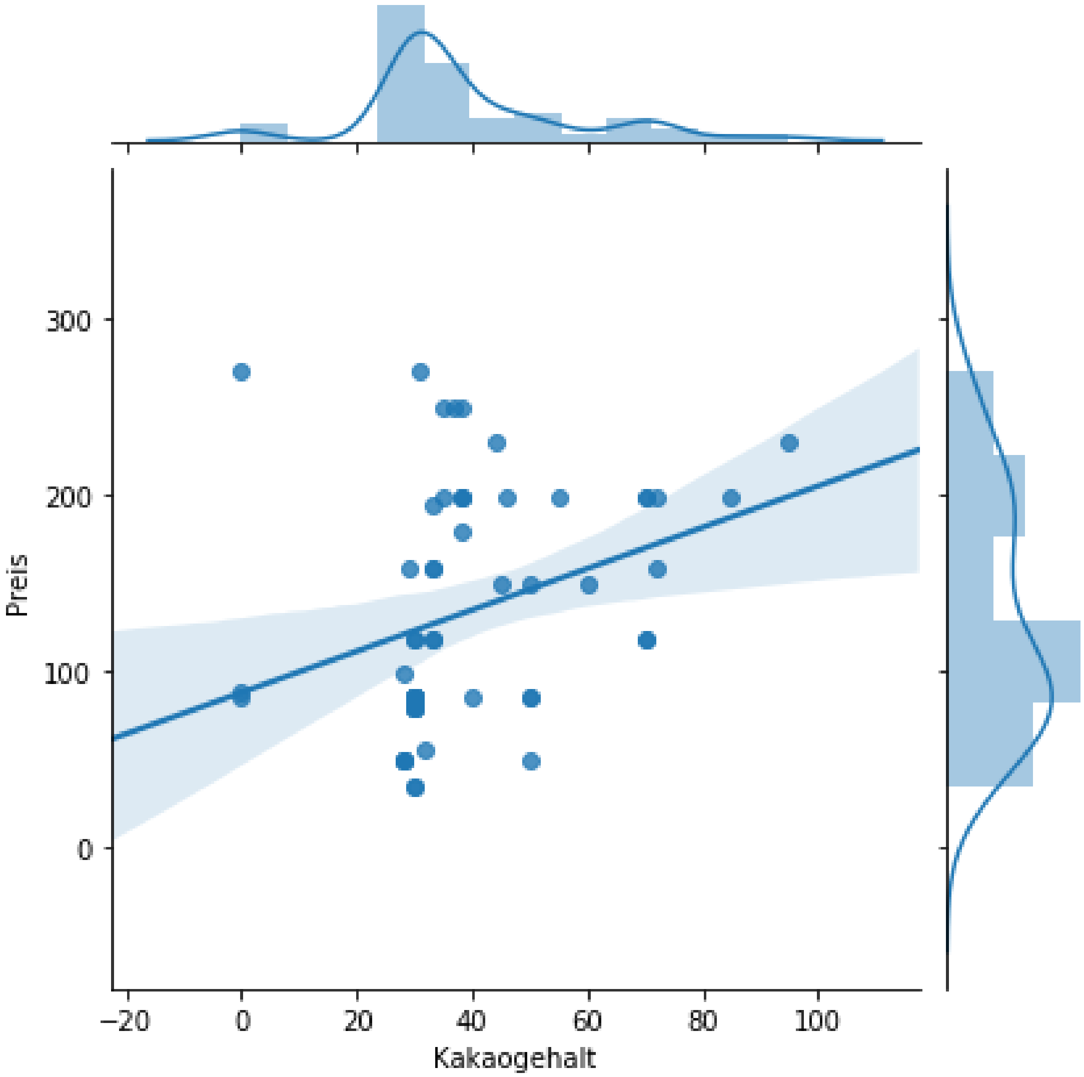
```
In [22]: # use the function regplot to make a scatterplot
         sns.regplot(x=schoko["Kakaogehalt"], y=schoko["Preis"], fit_reg=True)
```

```
Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1fc0ca5550>
```



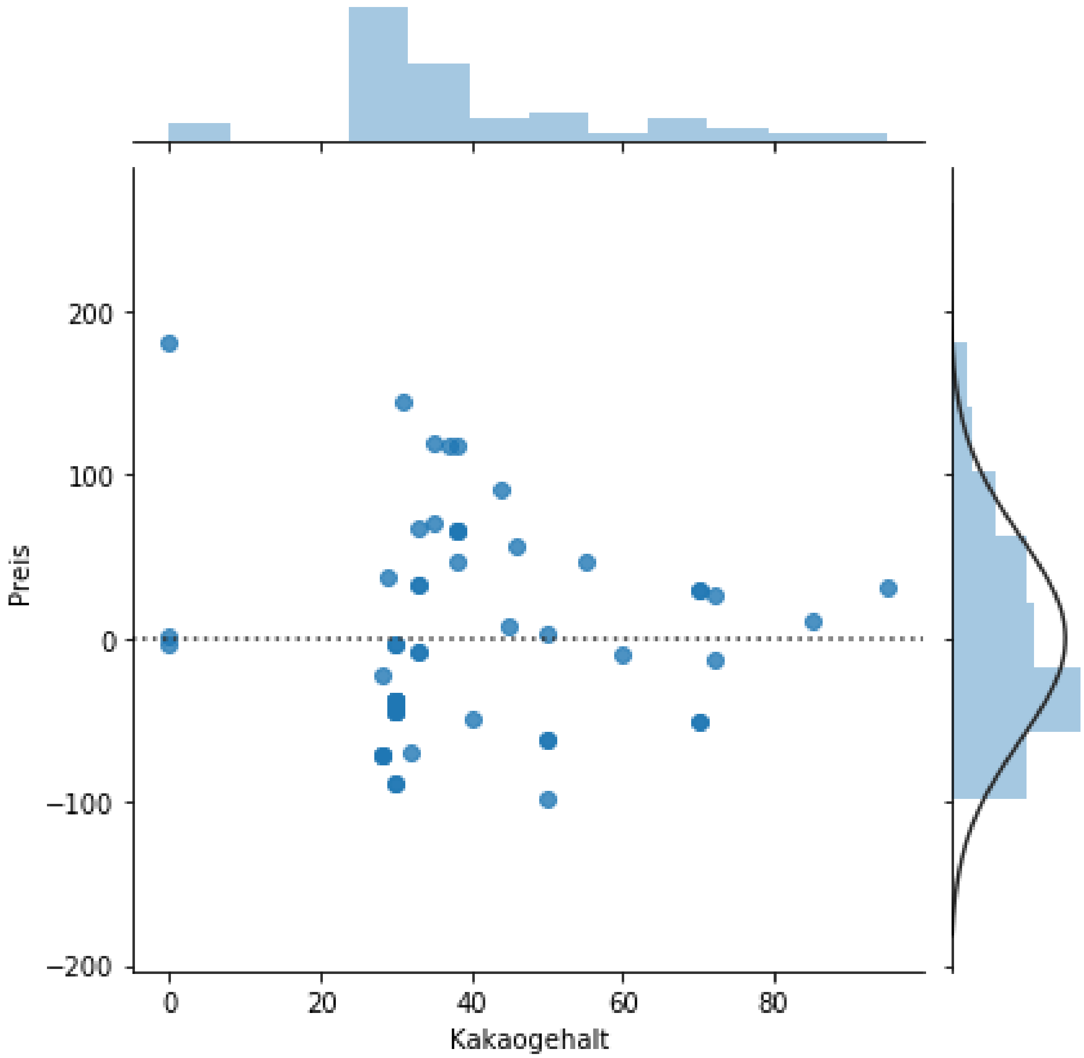

```
In [23]: # use the function regplot to make a scatterplot
         sns.jointplot(x=schoko["Kakaogehalt"], y=schoko["Preis"], kind="reg")
```

```
Out[23]: <seaborn.axisgrid.JointGrid at 0x7f1fe1c29828>
```



In [24]: # Plot the residuals
```
sns.jointplot(x=schoko["Kakaogehalt"], y=schoko["Preis"], kind="resid")
```

Out[24]: <seaborn.axisgrid.JointGrid at 0x7f1fc0b92780>

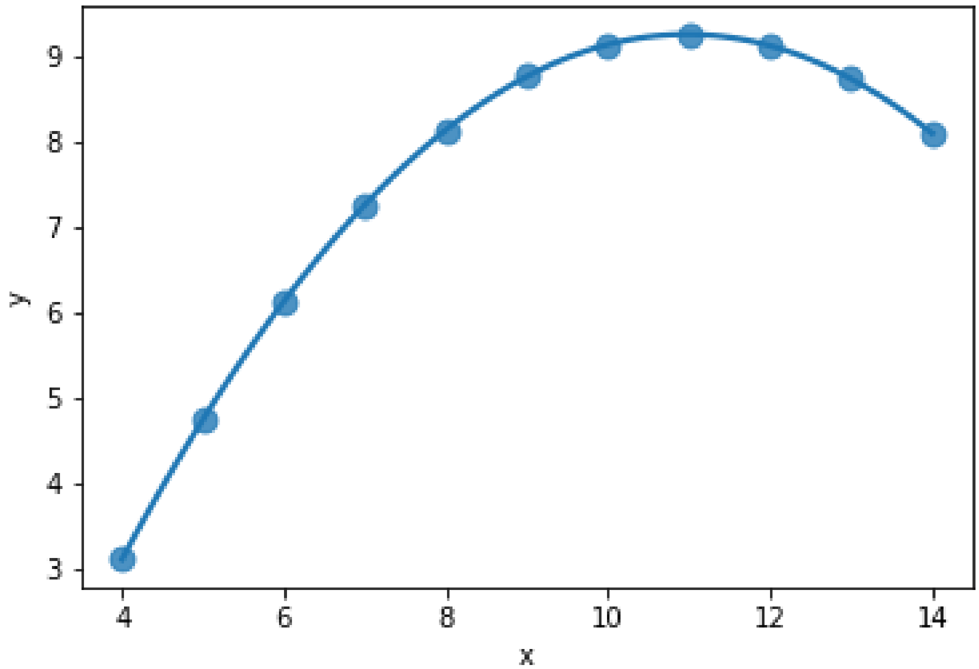



```
In [25]: import statsmodels.formula.api as smf

         # Fit the models, and show the results
         Res1 = smf.ols('Preis~Kakaogehalt', schoko).fit()
         Res1.summary()

Out[25]: <class 'statsmodels.iolib.summary.Summary'>
         """
                                     OLS Regression Results
         ==============================================================================
         Dep. Variable:                  Preis   R-squared:                       0.104
         Model:                            OLS   Adj. R-squared:                  0.088
         Method:                 Least Squares   F-statistic:                     6.626
         Date:                Mon, 18 Nov 2019   Prob (F-statistic):             0.0127
```

```
Time:                        14:04:14   Log-Likelihood:                -327.69
No. Observations:                  59   AIC:                             659.4
Df Residuals:                      57   BIC:                             663.5
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept      88.0130     19.553      4.501      0.000      48.859     127.167
Kakaogehalt     1.1707      0.455      2.574      0.013       0.260       2.081
==============================================================================
Omnibus:                        6.280   Durbin-Watson:                   0.624
Prob(Omnibus):                  0.043   Jarque-Bera (JB):                5.923
Skew:                           0.775   Prob(JB):                       0.0518
Kurtosis:                       3.077   Cond. No.                         102.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
"""
```

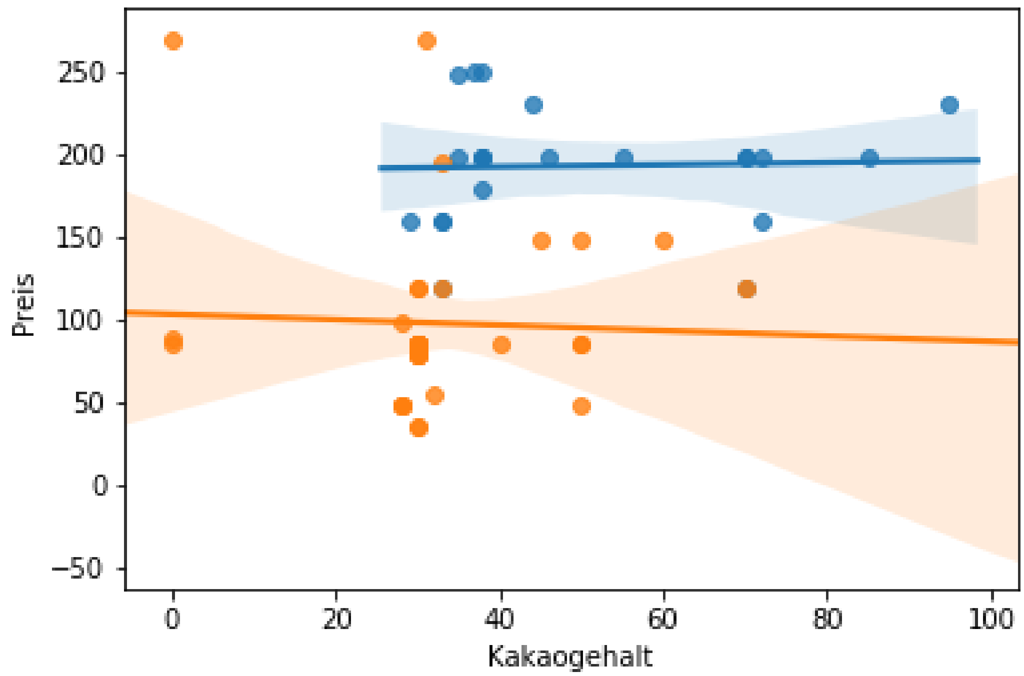
Plotte ein quadratisches Polynom mit regplot()

In [26]:
```python
# Load the anscombe dataset
ans = sns.load_dataset("anscombe")

# Select the 2nd dataset
data = ans.loc[ans.dataset == "II"]

# Create a regplot with a quadratic polynomial by setting order=2
ax = sns.regplot(x="x", y="y", data=data,
                 scatter_kws={"s": 80},
                 order=2, ci=None, truncate=True)
```



Unterscheidet sich die Beziehung zwischen Kakaogehalt und Preis für Bio und Nicht-Bio Schokolade?

```
In [27]: import statsmodels.formula.api as smf

         bio = schoko[schoko["Bio"] == "ja"]
         non_bio = schoko[schoko["Bio"] == "nein"]

         sns.regplot(bio.Kakaogehalt, bio.Preis)
         sns.regplot(non_bio.Kakaogehalt, non_bio.Preis)
         plt.show()

         # Fit the models, and show the results
         Res1 = smf.ols('Preis~Kakaogehalt', bio).fit()
         print(Res1.summary())

         Res2 = smf.ols('Preis~Kakaogehalt', non_bio).fit()
         print(Res2.summary())
```




```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Preis   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                 -0.049
Method:                 Least Squares   F-statistic:                   0.02396
Date:                Mon, 18 Nov 2019   Prob (F-statistic):              0.879
Time:                        14:04:14   Log-Likelihood:                -110.04
No. Observations:                  22   AIC:                             224.1
Df Residuals:                      20   BIC:                             226.3
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept     190.0249     22.472      8.456      0.000     143.150     236.900
Kakaogehalt     0.0647      0.418      0.155      0.879      -0.807       0.937
==============================================================================
Omnibus:                        0.607   Durbin-Watson:                   1.292
Prob(Omnibus):                  0.738   Jarque-Bera (JB):                0.416
Skew:                          -0.316   Prob(JB):                        0.812
Kurtosis:                       2.768   Cond. No.                         150.
==============================================================================

Warnings:
```

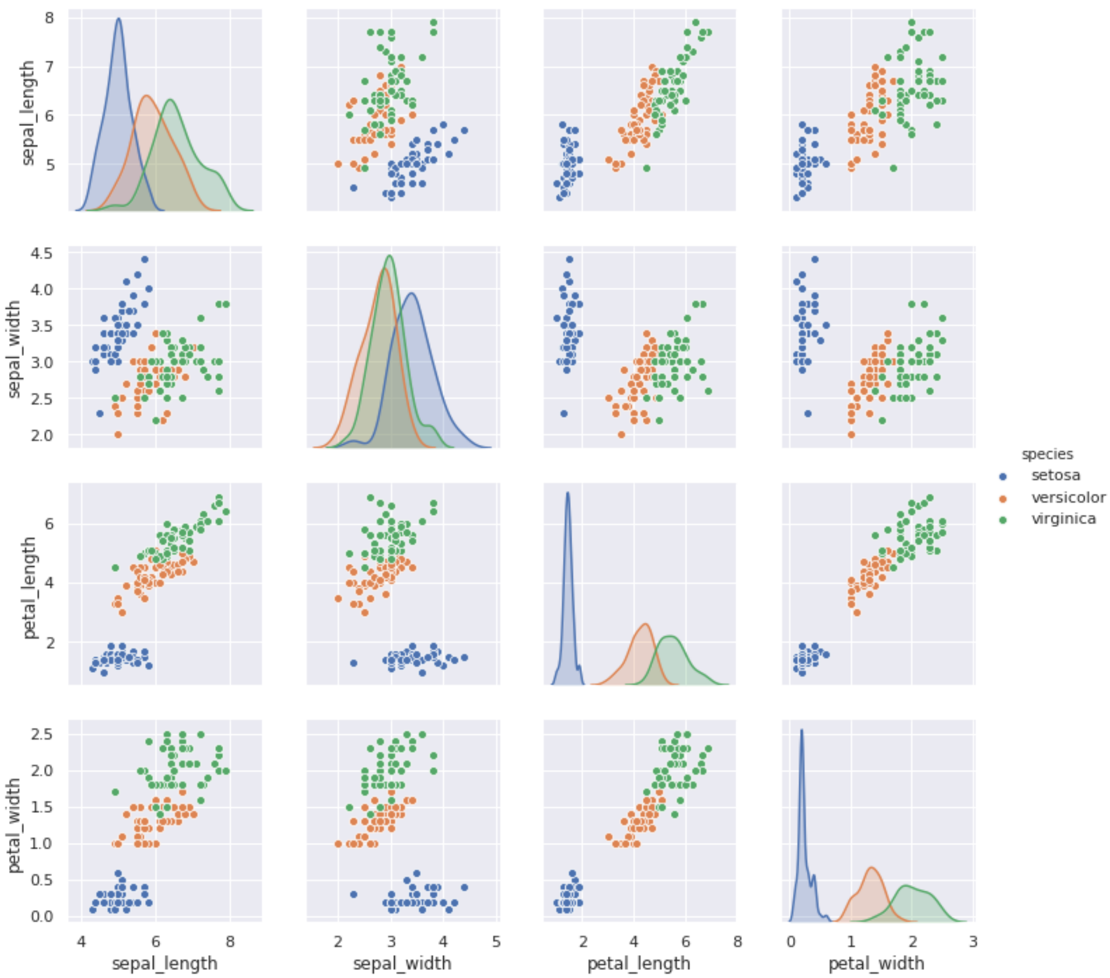
```
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Preis   R-squared:                       0.002
Model:                            OLS   Adj. R-squared:                 -0.027
Method:                 Least Squares   F-statistic:                   0.06471
Date:                Mon, 18 Nov 2019   Prob (F-statistic):              0.801
Time:                        14:04:14   Log-Likelihood:                -199.35
No. Observations:                  37   AIC:                             402.7
Df Residuals:                      35   BIC:                             405.9
Df Model:                           1
Covariance Type:            nonrobust
===============================================================================
                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------
Intercept     103.4833     22.849      4.529      0.000      57.097     149.869
Kakaogehalt    -0.1657      0.652     -0.254      0.801      -1.488       1.157
==============================================================================
Omnibus:                       23.649   Durbin-Watson:                   0.355
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               36.295
Skew:                           1.796   Prob(JB):                     1.31e-08
Kurtosis:                       6.263   Cond. No.                         89.6
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

1.4 Multivariate Datenanalyse

1.4.1 Korrelation

Pairs plot

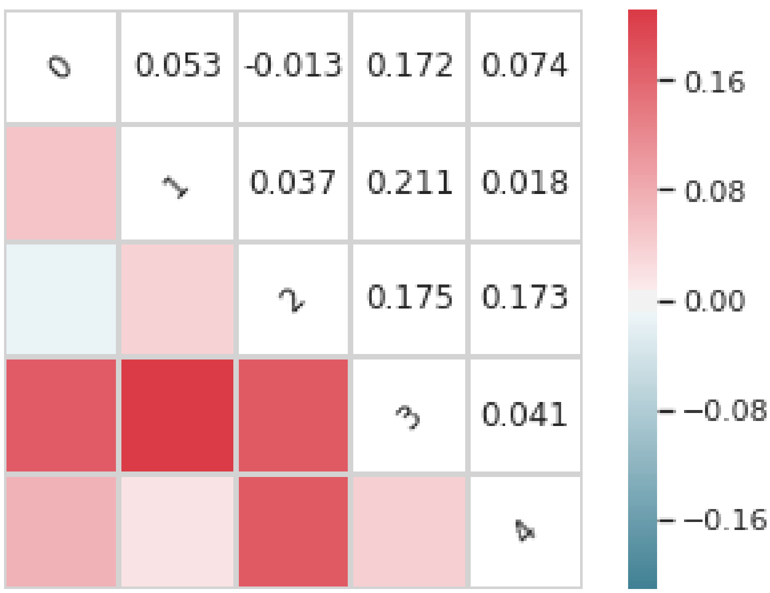
```
In [28]: import seaborn as sns
         sns.set()
         df = sns.load_dataset("iris")
         sns.pairplot(df, hue="species", height=2.5)

Out[28]: <seaborn.axisgrid.PairGrid at 0x7f1ff00b2828>
```



Korrelationsmatrix

```
In [29]: import numpy as np
         import pandas as pd
         import seaborn as sns
         import matplotlib.pyplot as plt
         sns.set(style="darkgrid")

         # Set seed for the random numbr generation
         rs = np.random.RandomState(33)
         # Create normally distribued dummy data,
         # simulating 100 recordings from 10 different variables
         d = rs.normal(size=(100, 5))
         d = pd.DataFrame(d)

         # Compute the correlation matrix
         corr = d.corr()
         #print(corr)
```

```
# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
fig, ax = plt.subplots()
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
vmax = np.abs(corr.values[~mask]).max()
sns.heatmap(corr, mask=mask, cmap=cmap, vmin=-vmax, vmax=vmax,
            square=True, linecolor="lightgray", linewidths=1, ax=ax)
for i in range(len(corr)):
    ax.text(i+0.5,(i+0.5), corr.columns[i], ha="center", va="center", rotation=45)
    for j in range(i+1, len(corr)):
        s = "{:.3f}".format(corr.values[i,j])
        ax.text(j+0.5,(i+0.5),s,
            ha="center", va="center")
ax.axis("off")
plt.show()
```



1.4.2 Multilineare Regression

```
In [30]: import pandas as pd
         import seaborn as sns
```

```
from statsmodels.formula.api import ols

data = sns.load_dataset("iris")

model = ols('sepal_width ~ species + petal_length', data).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:            sepal_width   R-squared:                       0.486
Model:                            OLS   Adj. R-squared:                  0.476
Method:                 Least Squares   F-statistic:                     46.08
Date:                Mon, 18 Nov 2019   Prob (F-statistic):           5.14e-21
Time:                        14:04:16   Log-Likelihood:                -37.808
No. Observations:                 150   AIC:                             83.62
Df Residuals:                     146   BIC:                             95.66
Df Model:                           3
Covariance Type:            nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
Intercept                 2.9919      0.099     30.206      0.000       2.796       3.188
species[T.versicolor]    -1.4927      0.181     -8.264      0.000      -1.850      -1.136
species[T.virginica]     -1.6741      0.255     -6.557      0.000      -2.179      -1.170
petal_length              0.2983      0.060      4.932      0.000       0.179       0.418
==============================================================================
Omnibus:                        3.167   Durbin-Watson:                   1.771
Prob(Omnibus):                  0.205   Jarque-Bera (JB):                3.214
Skew:                          -0.121   Prob(JB):                        0.200
Kurtosis:                       3.675   Cond. No.                         54.0
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Post-Hoc Analyse

```
In [31]: print(model.f_test([0, 1, -1, 0]))
```

```
<F test: F=array([[3.26191465]]), p=0.07296614041660325, df_denom=146, df_num=1>
```

1.4.3 Daten-Vorbereitung

z-Transformation

```
In [32]: import math
```

```
def z_transform(array):
  n = len(array)
  mn = sum(array)/n
  var = (1/(n-1))*sum(map(lambda xi: (xi-mn)**2, array))
  std = math.sqrt(var)
  z = [(xi-mn)/std for xi in array]
  return z

pizza_de = [4.99, 7.99, 5.99, 4.99, 6.99]
pizza_us = [5.74, 9.19, 6.89, 5.74, 8.04]

z_de = z_transform(pizza_de)
z_us = z_transform(pizza_us)
print(z_de)
print(z_us)
z_de == z_us
```

```
[-0.9203579866168446, 1.3805369799252667, -0.15339299776947424, -0.9203579866168446, 0.6135719
[-0.9203579866168446, 1.3805369799252667, -0.1533929977694744, -0.9203579866168446, 0.61357199
```

```
Out[32]: False
```

1.4.4 Cluster-Analyse

Euclidean Distance

```
In [33]: ### Euclidean distance matrix

         # Import libraries
         import scipy.spatial.distance as sp

         # Filtering survey data
         data = data[["sepal_length", "sepal_width", "petal_length", "petal_width"]]

         # Calculate distance
         dist = sp.pdist(data, 'euclidean')

         # Turn into DataFrame
         df_dist = pd.DataFrame(sp.squareform(dist))

         # Print head
         print(df_dist.head())
```

```
          0         1         2         3         4         5         6    \
0  0.000000  0.538516  0.509902  0.648074  0.141421  0.616441  0.519615
1  0.538516  0.000000  0.300000  0.331662  0.608276  1.090871  0.509902
2  0.509902  0.300000  0.000000  0.244949  0.509902  1.086278  0.264575
3  0.648074  0.331662  0.244949  0.000000  0.648074  1.166190  0.331662
```

```
4  0.141421  0.608276  0.509902  0.648074  0.000000  0.616441  0.458258

          7         8         9  ...       140       141       142       143  \
0  0.173205  0.921954  0.469042  ...  5.019960  4.636809  4.208325  5.257376
1  0.424264  0.509902  0.173205  ...  5.072475  4.702127  4.180909  5.320714
2  0.412311  0.435890  0.316228  ...  5.228767  4.868265  4.334743  5.475400
3  0.500000  0.300000  0.316228  ...  5.104900  4.760252  4.177320  5.349766
4  0.223607  0.921954  0.529150  ...  5.061620  4.686150  4.246175  5.297169

        144       145       146       147       148       149
0  5.136146  4.654031  4.276681  4.459821  4.650806  4.140048
1  5.206726  4.700000  4.249706  4.498889  4.718050  4.153312
2  5.353504  4.864155  4.430576  4.661545  4.848711  4.298837
3  5.232590  4.745524  4.288356  4.533211  4.719110  4.149699
4  5.173007  4.701064  4.330127  4.504442  4.678675  4.173727

[5 rows x 150 columns]
```

Jaccard similarity

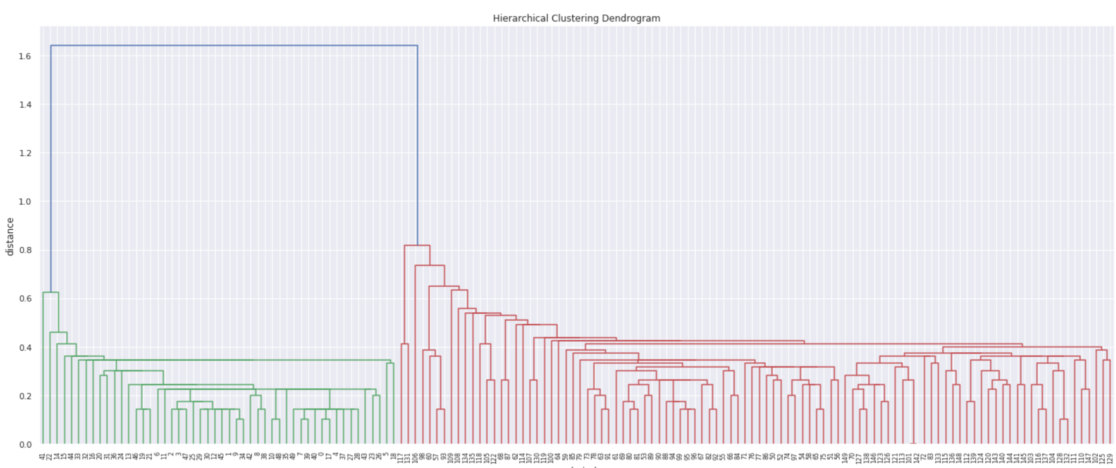
```
In [34]: # Calculate Jaccard similarity

         dist = sp.pdist(data, 'jaccard')
         df_dist = pd.DataFrame(sp.squareform(dist))
         print(df_dist.head())
```

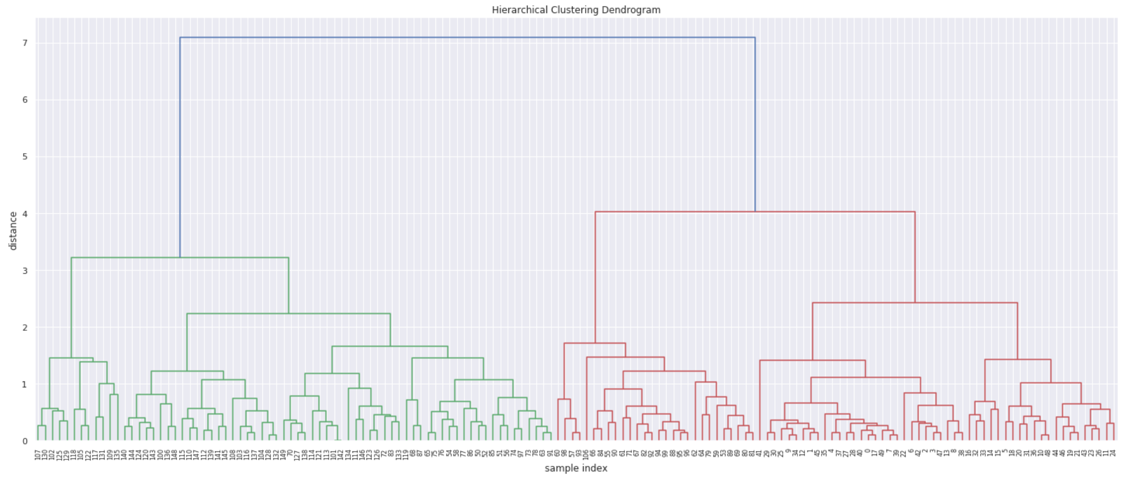
```
      0     1     2     3     4    5     6     7     8     9  ...   140   141  \
0  0.00  0.50  0.75  0.75  0.50  1.0  0.75  0.75  0.50  1.00  ...  1.00  1.00
1  0.50  0.00  0.75  0.75  0.50  1.0  0.75  0.75  0.50  0.75  ...  1.00  1.00
2  0.75  0.75  0.00  0.75  0.75  1.0  1.00  0.75  0.75  1.00  ...  1.00  1.00
3  0.75  0.75  0.75  0.00  0.75  1.0  0.75  0.50  0.75  0.50  ...  0.75  0.75
4  0.50  0.50  0.75  0.75  0.00  1.0  0.75  0.50  0.50  1.00  ...  1.00  1.00

   142   143  144   145  146   147  148   149
0  1.0  1.00  1.0  1.00  1.0  1.00  1.0  1.00
1  1.0  1.00  1.0  0.75  1.0  0.75  1.0  0.75
2  1.0  0.75  1.0  1.00  1.0  1.00  1.0  1.00
3  1.0  1.00  1.0  1.00  1.0  1.00  1.0  1.00
4  1.0  1.00  1.0  1.00  1.0  1.00  1.0  1.00

[5 rows x 150 columns]
```

Hierarchical clustering

```
In [35]: ### Hierarchical clustering
         from matplotlib import pyplot as plt
         from scipy.cluster.hierarchy import dendrogram, linkage
```

```
    Z_single = linkage(data, 'single') # Single linkage

    Z_complete = linkage(data, 'complete') # Complete linkage

In [36]: # Single-linkage clustering (method= single)

    # Calculate full dendrogram
    plt.figure(figsize=(25, 10))
    plt.title('Hierarchical Clustering Dendrogram')
    plt.xlabel('sample index')
    plt.ylabel('distance')
    dendrogram(Z_single,
               leaf_rotation=90., # rotates the x axis labels
               leaf_font_size=8., # font size for the x axis labels
    )
    plt.show()

    # Complete-linkage clustering (method= complete)
    plt.figure(figsize=(25, 10))
    plt.title('Hierarchical Clustering Dendrogram')
    plt.xlabel('sample index')
    plt.ylabel('distance')
    dendrogram(Z_complete,
               leaf_rotation=90., # rotates the x axis labels
               leaf_font_size=8., # font size for the x axis labels
    )
    plt.show()
```



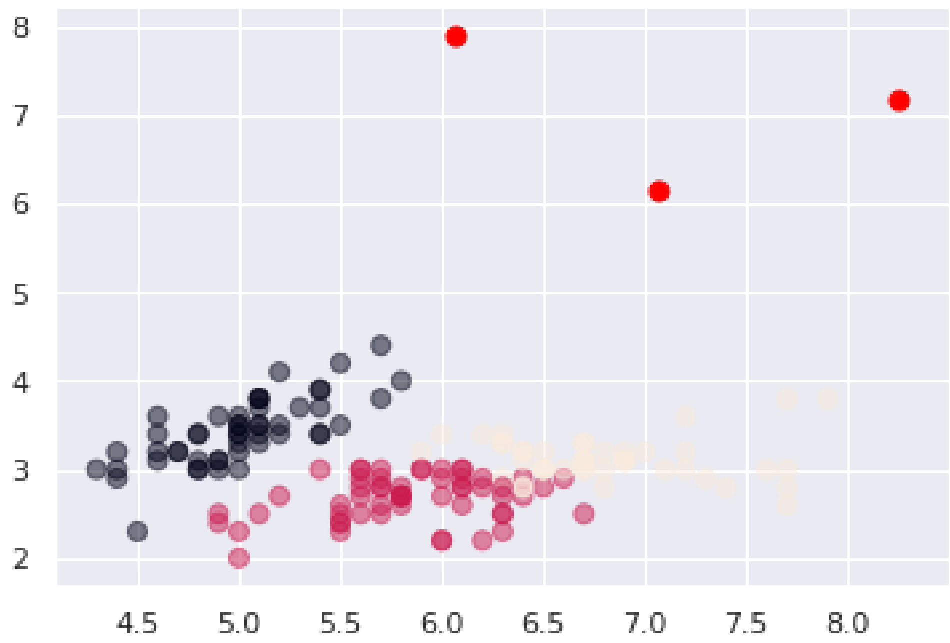


Non-hierarchical clustering

```
In [37]: ### Clustering with k-means

         # Import modules
         from scipy.cluster.vq import whiten
         from sklearn.cluster import KMeans

         # Normalize variables values
         std_survey_data = whiten(data, check_finite=True)

         # K-means cluster analysis
         kmeans = KMeans(n_clusters=3).fit(std_survey_data)
         centroids = kmeans.cluster_centers_
         print(centroids)

         # Plot data coloured by Clusters
         plt.scatter(data['sepal_length'], data['sepal_width'], c= kmeans.labels_.astype(float
         plt.scatter(centroids[:, 0], centroids[:, 1], c='red', s=50)
```

```
[[6.06566359 7.89114515 0.83096318 0.32381517]
 [7.06884701 6.16187415 2.51302623 1.88986207]
 [8.24767664 7.18318546 3.13897608 2.60871056]]
```

```
Out[37]: <matplotlib.collections.PathCollection at 0x7f1fbc9f5908>
```



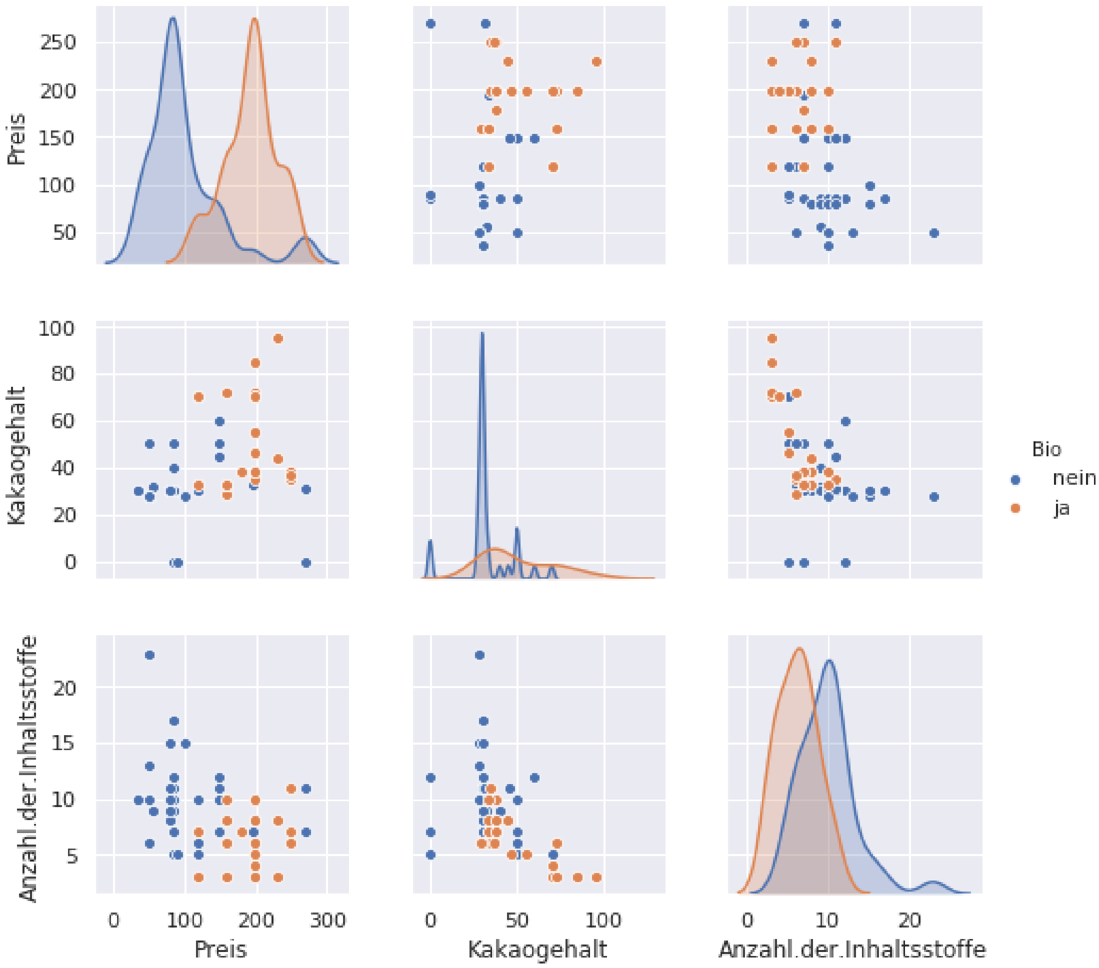
1.5 Übung II

Ladet den Datensatz **schoko.csv** in Python

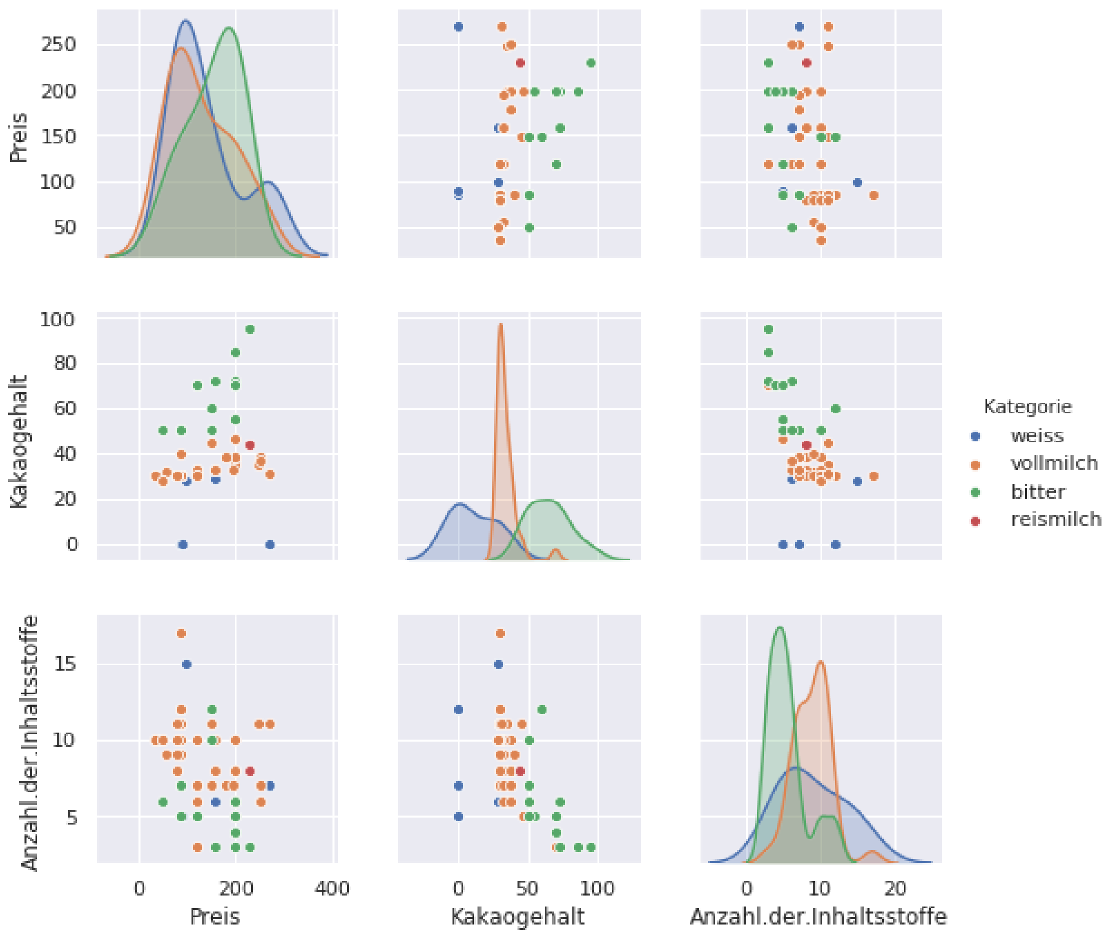
```
In [38]: import pandas as pd
         schoko = pd.read_csv("/home/matt/Documents/Github/pyStats/data/schoko.csv")
```

Erstelle einen pairplot() für Preis, Kakaogehalt und Anzahl der Inhaltsstoffe und zusätzlich "Bio" oder "Kategorie" als Farbton (hue)

```
In [39]: import seaborn as sns
         sns.pairplot(schoko, vars=["Preis", "Kakaogehalt", "Anzahl.der.Inhaltsstoffe"], hue="B

/home/matt/anaconda3/lib/python3.7/site-packages/statsmodels/nonparametric/kde.py:448: RuntimeW
  X = X[np.logical_and(X > clip[0], X < clip[1])] # won't work for two columns.
/home/matt/anaconda3/lib/python3.7/site-packages/statsmodels/nonparametric/kde.py:448: RuntimeW
  X = X[np.logical_and(X > clip[0], X < clip[1])] # won't work for two columns.


Out[39]: <seaborn.axisgrid.PairGrid at 0x7f1fbe46f3c8>
```



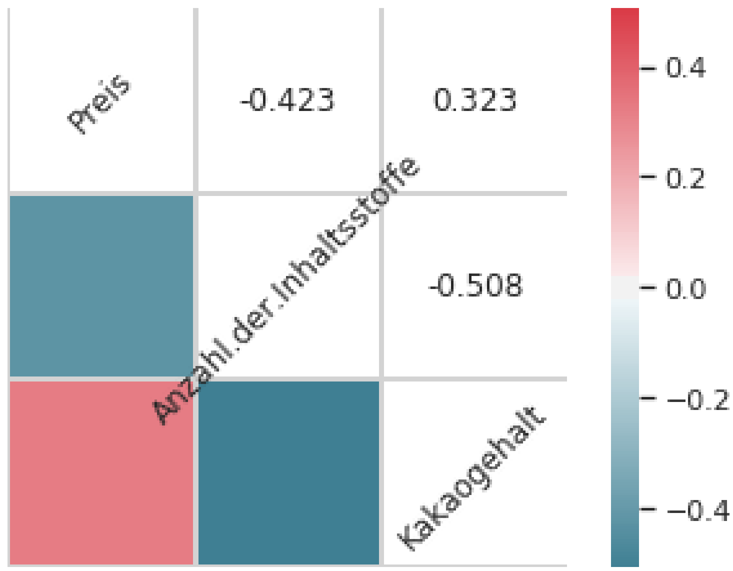

```
In [40]: import seaborn as sns
         sns.pairplot(schoko, vars=["Preis", "Kakaogehalt", "Anzahl.der.Inhaltsstoffe"], hue="I

/home/matt/anaconda3/lib/python3.7/site-packages/numpy/core/_methods.py:140: RuntimeWarning: De
  keepdims=keepdims)
/home/matt/anaconda3/lib/python3.7/site-packages/numpy/core/_methods.py:132: RuntimeWarning: in
  ret = ret.dtype.type(ret / rcount)


Out[40]: <seaborn.axisgrid.PairGrid at 0x7f1fbd554f60>
```



Erstelle eine Korrelationsmatrix für alle Variablen

```
In [41]: # Compute the correlation matrix
         import numpy as np
         from matplotlib import pyplot as plt

         schoko_sub = schoko[["Preis", "Kategorie", "Bio", "Anzahl.der.Inhaltsstoffe", "Kakaoge

         corr = schoko_sub.corr()
         #print(corr)

         # Generate a mask for the upper triangle
         mask = np.zeros_like(corr, dtype=np.bool)
         mask[np.triu_indices_from(mask)] = True

         # Set up the matplotlib figure
         fig, ax = plt.subplots()
         cmap = sns.diverging_palette(220, 10, as_cmap=True)
```

```
# Draw the heatmap with the mask and correct aspect ratio
vmax = np.abs(corr.values[~mask]).max()
sns.heatmap(corr, mask=mask, cmap=cmap, vmin=-vmax, vmax=vmax,
            square=True, linecolor="lightgray", linewidths=1, ax=ax)
for i in range(len(corr)):
    ax.text(i+0.5,(i+0.5), corr.columns[i], ha="center", va="center", rotation=45)
    for j in range(i+1, len(corr)):
        s = "{:.3f}".format(corr.values[i,j])
        ax.text(j+0.5,(i+0.5),s,
            ha="center", va="center")
ax.axis("off")
plt.show()
```



Erstelle eine multilineare Regression für Kakaogehalt, Anzahl der Inhaltsstoffe und Preis und plottet diesen Zusammenhang in 3D

```
In [42]: # OLS cannot deal with "Anzahl.der.Inhaltsstoffe", thus we have to rename the column
         schoko["Anzahl_Inhaltsstoffe"] = schoko["Anzahl.der.Inhaltsstoffe"]
```

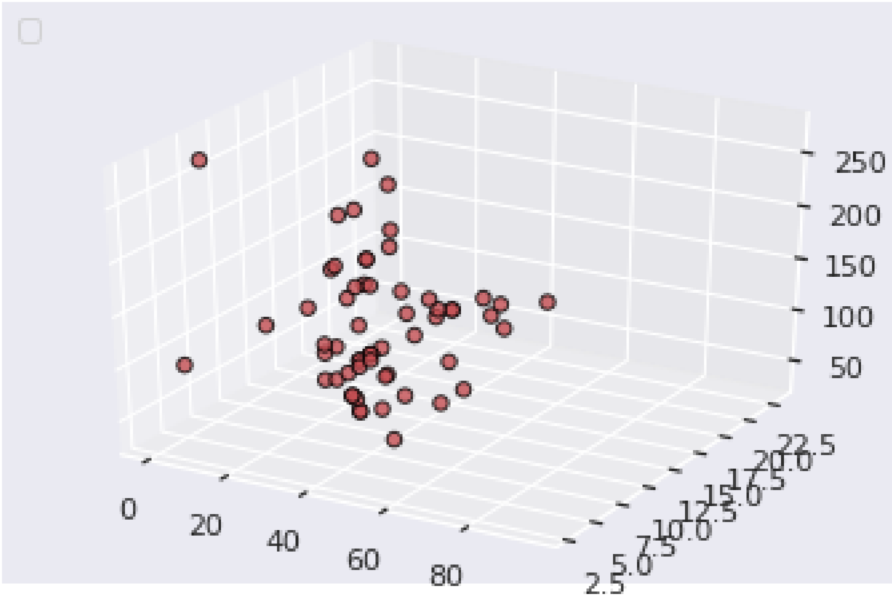
```
model = ols('Preis ~ Kakaogehalt + Anzahl_Inhaltsstoffe', schoko).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  Preis   R-squared:                       0.194
Model:                            OLS   Adj. R-squared:                  0.165
Method:                 Least Squares   F-statistic:                     6.749
Date:                Mon, 18 Nov 2019   Prob (F-statistic):            0.00237
Time:                        14:04:21   Log-Likelihood:                -324.56
No. Observations:                  59   AIC:                             655.1
Df Residuals:                      56   BIC:                             661.4
Df Model:                           2
Covariance Type:            nonrobust
========================================================================================
                           coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------------
Intercept              168.0088     37.042      4.536      0.000      93.805     242.212
Kakaogehalt              0.5288      0.505      1.047      0.300      -0.483       1.541
Anzahl_Inhaltsstoffe    -6.3620      2.543     -2.502      0.015     -11.455      -1.269
==============================================================================
Omnibus:                        4.410   Durbin-Watson:                   0.705
Prob(Omnibus):                  0.110   Jarque-Bera (JB):                3.982
Skew:                           0.636   Prob(JB):                        0.137
Kurtosis:                       2.999   Cond. No.                         204.
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

```
In [43]: import numpy as np
         import matplotlib.pyplot as plt
         from mpl_toolkits.mplot3d import axes3d

         # Create plot
         fig = plt.figure()
         ax = fig.add_subplot(1, 1, 1)
         ax = fig.gca(projection='3d')

         ax.scatter(schoko["Kakaogehalt"], schoko["Anzahl_Inhaltsstoffe"], schoko["Preis"],
                    alpha=0.8, c="r", marker="o", edgecolors='none', s=30)
         plt.legend(loc=2)
         plt.show()
```

```
/home/matt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:8: UserWarning: Requeste
```

```
/home/matt/anaconda3/lib/python3.7/site-packages/matplotlib/figure.py:98: MatplotlibDeprecatio
Adding an axes using the same arguments as a previous axes currently reuses the earlier instanc
  "Adding an axes using the same arguments as a previous axes "
No handles with labels found to put in legend.
```



Erstelle eine hierarchische Cluster-Analyse für jede Schokoladen-Tafel

In [44]:
```
# Move me column to index
#schoko.set_index("me", inplace=True)
schoko.head()
```

Out[44]:
```
                          me      Marke Einkaufsort  Preis  Kategorie   Bio  \
0     Choceur Weisse Crisp    Choceur        Aldi     99      weiss  nein
1  Choceur Alpenvollmilch    Choceur        Aldi     35  vollmilch  nein
2        Choceur Haselnuss    Choceur        Aldi     35  vollmilch  nein
3                Nusskcker  Nusskcker        Aldi     55  vollmilch  nein
4          Happy Halloween      Meybo     Bio Bio    199  vollmilch    ja

   Fair  crisp  nuss  traube  ...  chili  echte.vanille  cocos  Kakaogehalt  \
0  nein      1     0       0  ...      0              0      0         28.0
1  nein      0     0       0  ...      0              0      0         30.0
2  nein      0     1       0  ...      0              0      0         30.0
3  nein      0     1       0  ...      0              0      0         32.0
4  nein      0     0       0  ...      0              1      0         35.0

   Gewicht  Anzahl.der.Inhaltsstoffe  Nussanteil  Crisps  Verfallsdatum  \
0      200                        15        12.0       6            5.0
```

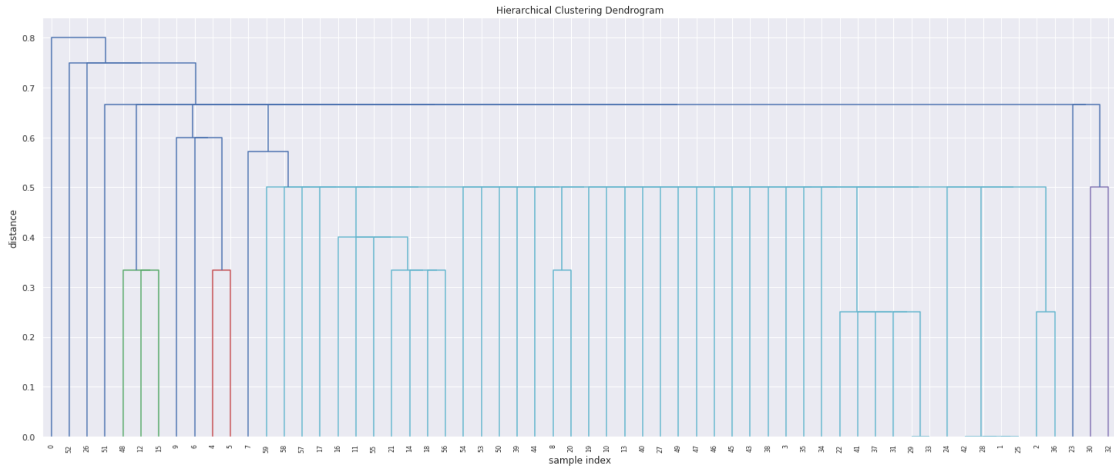
1	100	10	0.0	0	9.0
2	100	10	12.0	0	9.0
3	100	9	25.0	0	6.0
4	100	6	0.0	0	15.0

	Anzahl_Inhaltsstoffe
0	15
1	10
2	10
3	9
4	6

[5 rows x 21 columns]

In [45]:
```
### Hierarchical clustering
from matplotlib import pyplot as plt
from scipy.cluster.hierarchy import dendrogram, linkage

schoko_sub = schoko[["crisp", "nuss", "traube", "rum", "chili", "echte.vanille", "coco

Z_single = linkage(schoko_sub, 'single', metric="jaccard") # Single linkage
#Z_single = linkage(schoko, 'single', metric="cosine") # Single linkage

#?linkage
#?pdist
```

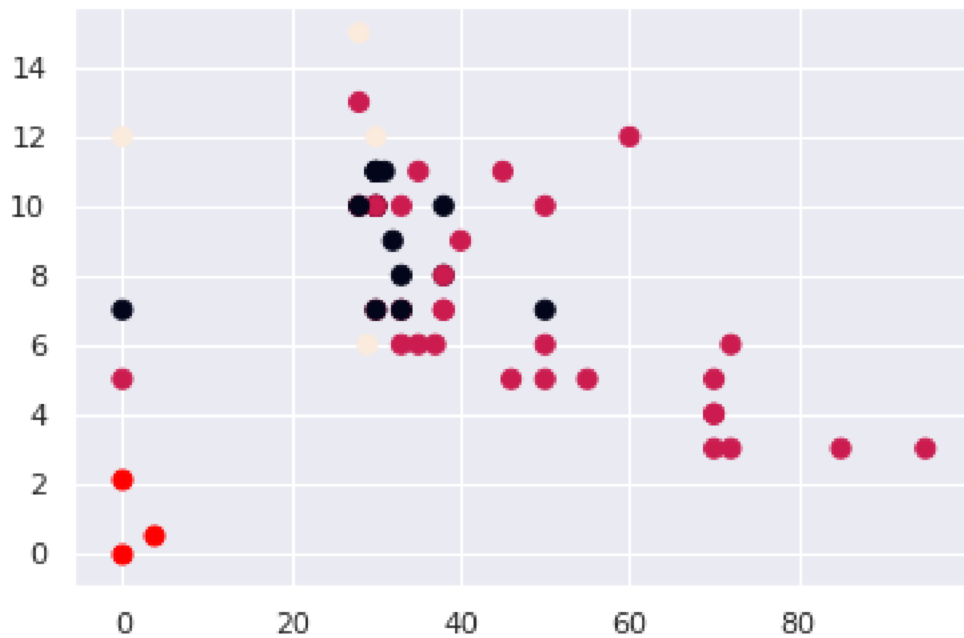
In [46]:
```
# Calculate full dendrogram
plt.figure(figsize=(25, 10))
plt.title('Hierarchical Clustering Dendrogram')
plt.xlabel('sample index')
plt.ylabel('distance')
dendrogram(Z_single,
           leaf_rotation=90., # rotates the x axis labels
           leaf_font_size=8., # font size for the x axis labels

)
plt.show()
```



Erstelle eine nicht-hierarchische Cluster-Analyse für den Schoko Datensatz

In [47]:
```
### Clustering with k-means

# Import modules
from scipy.cluster.vq import whiten
from sklearn.cluster import KMeans

# Normalize variables values
schoko_sub = schoko_sub.dropna()
std_survey_data = whiten(schoko_sub, check_finite=True)

# K-means cluster analysis
kmeans = KMeans(n_clusters=3).fit(std_survey_data)
centroids = kmeans.cluster_centers_
#print(centroids)
schoko_sub.head()

# Plot data coloured by Clusters
plt.scatter(schoko_sub['Kakaogehalt'], schoko_sub['Anzahl.der.Inhaltsstoffe'],
            c= kmeans.labels_.astype(float), s=50)#, alpha=0.5)
plt.scatter(centroids[:, 0], centroids[:, 1], c='red', s=50)
```

Out[47]:
```
<matplotlib.collections.PathCollection at 0x7f1fbc144ba8>
```


14
12
10
8
6
4
2
0
0
20
40
60
80