Draft Analysis

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1 Draft analysis

Group name: D

1.1 Introduction

This section includes an introduction to the project motivation, data, and research question. Include a data dictionary

1.2 Setup

```python
import pandas as pd
import altair as alt
import numpy as np
from pandas import DataFrame
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

alt.data_transformers.disable_max_rows() #aus Code overview Histogramm
from scipy import stats # to compute the mode

from sklearn.linear_model import LinearRegression #Fitting a line
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LassoCV
from sklearn.linear_model import Lasso

import matplotlib.pyplot as plt  # To visualize

import joblib
import time
```

1.2.0.1 Definition für linksbündige Darstellung

```
def left_align(df: DataFrame):
    left_aligned_df = df.style.set_properties(**{'text-align': 'left'})
    left_aligned_df = left_aligned_df.set_table_styles(
        [dict(selector='th', props=[('text-align', 'left')])]
    )
    return left_aligned_df
```

1.3 Data

1.4 Import data

```
df_bevoelkerung = pd.read_csv(
    '../references/csv_Bevoelkerung/Zensus11_Datensatz_Bevoelkerung.csv',
    delimiter=';',
    dtype={
        'AGS_12': 'category',
        'RS_Land': 'category',
        'RS_RB_NUTS2': 'category',
        'RS_Kreis': 'category',
        'RS_VB': 'category',
        'RS_Gem': 'category',
        'Name': 'category',
        'Reg_Hier': 'category'
    }
)
```

```
/var/folders/k5/1ngg2lrs0p51m_z5s1q72vv00000gn/T/ipykernel_58605/3067287871.py:1: DtypeWarni
  df_bevoelkerung = pd.read_csv(
```

1.4.1 Data structure

```
df_bevoelkerung.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12544 entries, 0 to 12543
```

```
Columns: 223 entries, AGS_12 to BIL_5.8
dtypes: category(8), float64(41), int64(8), object(166)
memory usage: 21.4+ MB
```

1.4.2 Data corrections

Datatype Korrekturen durchführen, sodass danach nur noch Category oder float vorhanden ist: - interger in float verwandeln - / und - in 0-Werte verwandeln, da diese im engeren Sinne als 0 zählen - Zahlen in Klammern als normale Zahlen verwandeln

```
# integers in float verwandeln
for column in df_bevoelkerung.select_dtypes(['int64']):
    df_bevoelkerung[column] = df_bevoelkerung[column].astype('float64')

df_bevoelkerung = df_bevoelkerung.replace('/',0)
df_bevoelkerung = df_bevoelkerung.replace('-', 0)

for column in df_bevoelkerung.select_dtypes('object'):
    df_bevoelkerung[column]=df_bevoelkerung[column].astype(str).str.extract('(\d+)').astyp
```

```
df_bevoelkerung.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12544 entries, 0 to 12543
Columns: 223 entries, AGS_12 to BIL_5.8
dtypes: category(8), float64(215)
memory usage: 21.4 MB
```

Check, ob Anpassung der Zahlung erfolgreich:

```
df_bevoelkerung.loc[df_bevoelkerung['Name'] == 'Barkenholm', ['DEM_2.7']]
```

	DEM_2.7
43	71.0

```
df_bevoelkerung.loc[df_bevoelkerung['Name']=='Bergewöhrden', ['DEM_2.10']]
```

	DEM_2.10
44	0.0

1.4.3 Variable lists

```
df_predictor_variables = pd.read_excel('../references/Predictor Variables Definition.xlsx'
```

```
left_align(df_predictor_variables)
```

Variable	Quote	Berechnung
Migrationshintergrund	Migrationsquote	(Anzahl Personen mit Migrationshintergrund / Anzahl Persone
Religionszugehörigkeit	Christenquote*	(Römisch-katholische Kirche + Evangelische Kirch) / Bevölkeru
Geschlecht	Männerquote	(Anzahl Männer / Einwohner gesamt)
Bildungsniveau	Akademikerquote**	(Fach- oder Berufsakademie + FH-Abschluss + Hochschulabsch
Stellung im Beruf	Beamtenquote	(Anzahl Beamter / Erwerbstätige insgesamt)
Familienstand	Singlequote***	(Anzahl Lediger + Verwitwete + Geschiedene + eingetragene L

1.4.3.1 Berechnung der Variablen im gesamten Dataset

```
df_bevoelkerung['Arbeitslosenquote'] = df_bevoelkerung['ERW_1.10'] / df_bevoelkerung['ERW_
df_bevoelkerung['Arbeitslosenquote2'] = (1-(df_bevoelkerung['ERW_1.7'] / df_bevoelkerung['
df_bevoelkerung['Migrationsquote'] = df_bevoelkerung['MIG_1.3'] / df_bevoelkerung['MIG_1.1
df_bevoelkerung['Migrationsquote2'] = (1-(df_bevoelkerung['MIG_1.2'] / df_bevoelkerung['MI
df_bevoelkerung['Christenquote'] = ((df_bevoelkerung['REL_1.2'] + df_bevoelkerung['REL_1.3
df_bevoelkerung['Männerquote'] = (df_bevoelkerung['DEM_1.2']  / df_bevoelkerung['DEM_1.1']
df_bevoelkerung['Akademikerquote'] = ((df_bevoelkerung['BIL_5.5'] + df_bevoelkerung['BIL_5
df_bevoelkerung['Beamtenquote'] = (df_bevoelkerung['ERW_2.3'] / df_bevoelkerung['ERW_2.1']
df_bevoelkerung['Singlequote'] = ((df_bevoelkerung['DEM_2.4'] + df_bevoelkerung['DEM_2.10'
```

```
df_bevoelkerung.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12544 entries, 0 to 12543
```

```
Columns: 232 entries, AGS_12 to Singlequote
dtypes: category(8), float64(224)
memory usage: 22.3 MB
```

```
df_bevoelkerung.head()
```

	AGS_12	RS_Land	RS_RB_NUTS2	RS_Kreis	RS_VB	RS_Gem	Name
0	0	0	NaN	NaN	NaN	NaN	Deutschland
1	1	1	NaN	NaN	NaN	NaN	Schleswig-Holstein
2	10010000000	1	0	1	0	0	Flensburg, Stadt
3	1001	1	0	1	NaN	NaN	Flensburg, Stadt
4	10020000000	1	0	2	0	0	Kiel, Landeshauptstadt

1.4.4 Data splitting

1.4.4.0.1 Dataframe auf relevante Spalten kürzen und auf Gemeinde bzw. Bundesländer filtern

Dataframe auf relevante Spalten filtern und in neues kopieren:

```
df_analyse = df_bevoelkerung.iloc[:, [6,7,223,224,225,226,227,228,229,230,231]].copy()
```

NaN entfernen:

```
df_analyse.dropna(inplace=True)
```

```
df_analyse
```

	Name	Reg_Hier	Arbeitslosenquote	Arbeitslosenq
0	Deutschland	Bund	4.652478	4.652501
1	Schleswig-Holstein	Land	4.578416	4.578416
2	Flensburg, Stadt	Gemeinde	6.657547	6.657547
3	Flensburg, Stadt	Stadtkreis/kreisfreie Stadt/Landkreis	6.657547	6.657547
4	Kiel, Landeshauptstadt	Gemeinde	7.539341	7.539341
...	...	...	...	...
12492	Zeulenroda-Triebes, Stadt	Gemeinde	5.662651	5.662651
12497	Altenburger Land	Stadtkreis/kreisfreie Stadt/Landkreis	7.879628	7.879628
12498	Altenburg, Stadt	Gemeinde	9.632751	9.632751

	Name	Reg_Hier	Arbeitslosenquote	Arbeitslosenq
12500	Meuselwitz, Stadt	Gemeinde	9.363958	9.363958
12502	Schmölln, Stadt	Gemeinde	6.430868	6.430868

Liste mit Prädikatoren:

```
predictor = df_analyse.iloc[:,5:11].columns.values.tolist()
predictor
```

```
['Migrationsquote2',
 'Christenquote',
 'Männerquote',
 'Akademikerquote',
 'Beamtenquote',
 'Singlequote']
```

Dataframe auf Hierarchie-Ebene **Gemeinde** filtern.

```
df_analyse_gemeinde = df_analyse[df_analyse['Reg_Hier']=='Gemeinde'].reset_index(drop=True
```

```
df_analyse_gemeinde
```

	Name	Reg_Hier	Arbeitslosenquote	Arbeitslosenquote2	Migrationsquote	M
0	Flensburg, Stadt	Gemeinde	6.657547	6.657547	15.957447	15
1	Kiel, Landeshauptstadt	Gemeinde	7.539341	7.539341	18.900021	18
2	Lübeck, Hansestadt	Gemeinde	7.158110	7.167394	16.812500	16
3	Neumünster, Stadt	Gemeinde	6.924644	6.899185	16.924489	16
4	Brunsbüttel, Stadt	Gemeinde	5.365854	5.365854	13.682565	13
...	...	...	...	...	...	...
1568	Greiz, Stadt	Gemeinde	6.813820	6.813820	2.112338	2.
1569	Zeulenroda-Triebes, Stadt	Gemeinde	5.662651	5.662651	3.547963	3.
1570	Altenburg, Stadt	Gemeinde	9.632751	9.632751	1.978736	1.
1571	Meuselwitz, Stadt	Gemeinde	9.363958	9.363958	2.098540	2.
1572	Schmölln, Stadt	Gemeinde	6.430868	6.430868	3.710095	3.

```
df_analyse_gemeinde.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1573 entries, 0 to 1572
Data columns (total 11 columns):
 #   Column               Non-Null Count  Dtype   
---  ------               --------------  -----   
 0   Name                 1573 non-null   category
 1   Reg_Hier             1573 non-null   category
 2   Arbeitslosenquote    1573 non-null   float64 
 3   Arbeitslosenquote2   1573 non-null   float64 
 4   Migrationsquote      1573 non-null   float64 
 5   Migrationsquote2     1573 non-null   float64 
 6   Christenquote        1573 non-null   float64 
 7   Männerquote          1573 non-null   float64 
 8   Akademikerquote      1573 non-null   float64 
 9   Beamtenquote         1573 non-null   float64 
 10  Singlequote          1573 non-null   float64 
dtypes: category(2), float64(9)
memory usage: 465.3 KB
```

```python
# define outcome variable as y_label
y_label = 'Arbeitslosenquote2'

# select features
features = predictor

# create feature data
X = df_analyse_gemeinde[features]

# create response
y = df_analyse_gemeinde[y_label]
```

1.4.4.1 Data Splitting - train & test data

```python
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.2,
                                                    random_state=42)
```

```python
# data exploration set
df_train = pd.DataFrame(X_train.copy())
df_train = df_train.join(pd.DataFrame(y_train))
```

```
df_train
```

	Migrationsquote2	Christenquote	Männerquote	Akademikerquote	Beamtenquote	Singlequote	A
1041	29.206142	73.971140	48.100815	18.275467	5.090006	53.898667	2
277	18.195158	80.491887	49.356036	10.834050	4.965517	52.041039	2
1223	33.358298	67.257531	47.849582	16.443128	3.807391	55.075046	3
925	21.221751	75.438658	48.500299	16.352459	5.246523	50.564366	1
1161	25.235602	85.163236	49.448950	10.391198	5.534351	50.207943	2
...	...	...	...	...	...	...	.
1130	19.279854	60.266185	46.379427	30.991957	5.922747	53.891270	3
1294	12.534626	81.905846	49.614947	12.569170	6.327373	51.597134	4
860	19.919110	65.085772	48.678103	16.607774	4.291045	50.232089	3
1459	4.362730	14.812994	48.360429	13.388544	2.231237	52.158948	1
1126	27.406765	67.395069	49.459883	18.365288	5.927052	59.627278	2

Dataframe auf Ebene Bundesland filtern:

```
df_analyse_bund = df_analyse[df_analyse['Reg_Hier']=='Land'].reset_index(drop=True)
```

```
df_analyse_bund
```

	Name	Reg_Hier	Arbeitslosenquote	Arbeitslosenquote2	Migrationsquote	Mig
0	Schleswig-Holstein	Land	4.578416	4.578416	12.024768	12.0
1	Hamburg	Land	5.664054	5.664054	28.301597	28.3
2	Niedersachsen	Land	4.401018	4.401018	16.725965	16.7
3	Bremen	Land	6.646302	6.646302	26.452131	26.4
4	Nordrhein-Westfalen	Land	5.095187	5.095187	24.451495	24.4
5	Hessen	Land	3.883143	3.883143	25.473128	25.4
6	Rheinland-Pfalz	Land	3.787513	3.787048	19.088275	19.0
7	Baden-Württemberg	Land	3.134949	3.134949	25.678058	25.6
8	Bayern	Land	2.853099	2.853099	19.116721	19.1
9	Saarland	Land	4.393987	4.395949	16.344238	16.3
10	Berlin	Land	8.555266	8.555266	24.069973	24.0
11	Brandenburg	Land	6.416525	6.417262	4.564780	4.56
12	Mecklenburg-Vorpommern	Land	7.664427	7.664427	3.812100	3.81
13	Sachsen	Land	6.528669	6.528669	4.388315	4.38
14	Sachsen-Anhalt	Land	7.835750	7.835750	3.755953	3.75
15	Thüringen	Land	5.669116	5.669116	3.531474	3.53

Variablen Migration:

```
variables_migration = ['Reg_Hier','Name','ERW_1.4','ERW_1.10','MIG_1.1','MIG_1.2','MIG_1.3
```

Variablen Religion:

```
variables_religion = ['Reg_Hier','Name','ERW_1.4','ERW_1.10','REL_1.1','REL_1.2','REL_1.3'
```

Variablen Geschlecht:

```
variables_geschlecht= ['Reg_Hier','Name','ERW_1.4','ERW_1.10','DEM_1.1','DEM_1.2','DEM_1.3
```

Variablen Bildung:

```
variables_bildung= ['Reg_Hier','Name','ERW_1.4','ERW_1.10','BIL_5.1','BIL_5.2','BIL_5.3','
```

Variablen Beruf:

```
variables_beruf = ['Reg_Hier','Name','ERW_1.4','ERW_1.10','ERW_2.1','ERW_2.2','ERW_2.3','E
```

Variablen Familien:

```
variables_familien = ['Reg_Hier','Name','ERW_1.4','ERW_1.10','DEM_2.1','DEM_2.4','DEM_2.7'
```

1.5 Analysis

1.5.1 Descriptive statistics

```
df_analyse_gemeinde.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Arbeitslosenquote	1573.0	4.129315	2.237428	0.000000	2.794760	3.618907	5.016766	16.871
Arbeitslosenquote2	1573.0	4.225062	2.100031	0.780031	2.796174	3.619303	5.022500	16.871
Migrationsquote	1573.0	17.750686	9.632732	0.000000	10.633649	17.838900	24.120116	53.932
Migrationsquote2	1573.0	17.752142	9.628915	0.850662	10.663616	17.836257	24.120116	53.982
Christenquote	1573.0	62.137232	20.945943	5.933338	58.604711	68.010543	75.942976	93.909
Männerquote	1573.0	48.697872	0.843340	45.102669	48.190799	48.702359	49.177376	54.993
Akademikerquote	1573.0	13.770178	5.853955	2.092871	9.776536	12.344777	16.242999	47.997
Beamtenquote	1573.0	5.067968	1.740783	1.236476	3.889789	4.892966	6.017192	18.870

	count	mean	std	min	25%	50%	75%	max
Singlequote	1573.0	52.214032	3.013940	44.397914	50.252657	51.690254	53.661406	66.4629

```
df_analyse_gemeinde_long = df_analyse_gemeinde.iloc[:,2:11].melt(var_name="Quotenname",val
df_analyse_gemeinde_long
```

	Quotenname	Quote
0	Arbeitslosenquote	6.657547
1	Arbeitslosenquote	7.539341
2	Arbeitslosenquote	7.158110
3	Arbeitslosenquote	6.924644
4	Arbeitslosenquote	5.365854
...	...	...
14152	Singlequote	53.023676
14153	Singlequote	51.721678
14154	Singlequote	53.276621
14155	Singlequote	49.872309
14156	Singlequote	51.456642

```
alt.Chart(df_analyse_gemeinde_long).mark_area(
    opacity=0.5,
    interpolate='step'
).encode(
    alt.X('Quote:Q', bin=alt.Bin(maxbins=50)),
    alt.Y('count()', stack=None),
    alt.Color('Quotenname:N'),
    tooltip = ['Quotenname']
).properties(
    title="Zusammenfassendes Histogramm der Quoten"
).interactive()
```

```
alt.Chart(...)
```

```
Quoten = df_analyse_gemeinde.iloc[:,2:12].columns.values.tolist()
```

```python
alt.Chart(df_analyse_gemeinde, width=200, height=150).mark_bar().encode(
    alt.X(alt.repeat("repeat"), type="quantitative", bin=True),
    y='count()'
).repeat(
    repeat=Quoten,
    columns=3
)
```

```
alt.RepeatChart(...)
```

```python
source = df_analyse_gemeinde
hist = alt.Chart(source).mark_bar().encode(
    x=alt.X("Arbeitslosenquote2",
            bin=True),
    y='count()',
)
```

```python
# Boxplot
box = alt.Chart(source).mark_boxplot().encode(
    x='Arbeitslosenquote2',
)
```

```python
alt.vconcat(hist, box)
```

```
alt.VConcatChart(...)
```

```python
df_analyse_gemeinde["Arbeitslosenquote2"].describe()
```

```
count    1573.000000
mean        4.225062
std         2.100031
min         0.780031
25%         2.796174
50%         3.619303
75%         5.022500
max        16.871705
Name: Arbeitslosenquote2, dtype: float64
```

```python
hist = alt.Chart(source).mark_bar().encode(
    alt.X(
        "Arbeitslosenquote2",
        bin=True,
        scale=alt.Scale(zero=True)
    ),
    alt.Y('count()')
)
box = alt.Chart(source).mark_boxplot().encode(
    x=alt.X(
        'Arbeitslosenquote2',
        scale=alt.Scale(zero=True)
    )
)

print(source['Arbeitslosenquote2'].describe())
alt.vconcat(hist, box,).properties(title='Übersicht Arbeitslosenquote').configure_title(fo
```

```
count    1573.000000
mean        4.225062
std         2.100031
min         0.780031
25%         2.796174
50%         3.619303
75%         5.022500
max        16.871705
Name: Arbeitslosenquote2, dtype: float64
```

```
alt.VConcatChart(...)
```

```python
hist = alt.Chart(source).mark_bar().encode(
    alt.X(
        "Migrationsquote",
        bin=True,
        scale=alt.Scale(zero=True)
    ),
    alt.Y('count()')
)
box = alt.Chart(source).mark_boxplot().encode(
    x=alt.X(
```

```
        'Migrationsquote',
        scale=alt.Scale(zero=True)
    )
)

print(source['Migrationsquote'].describe())
Migrationsquote = alt.vconcat(hist, box,).properties(title='Übersicht Migrationsquote').co
Migrationsquote
```

```
count    1573.000000
mean       17.750686
std         9.632732
min         0.000000
25%        10.633649
50%        17.838900
75%        24.120116
max        53.932014
Name: Migrationsquote, dtype: float64
```

```
alt.VConcatChart(...)
```

```
hist = alt.Chart(source).mark_bar().encode(
    alt.X(
        "Migrationsquote2",
        bin=True,
        scale=alt.Scale(zero=True)
    ),
    alt.Y('count()')
)
box = alt.Chart(source).mark_boxplot().encode(
    x=alt.X(
        'Migrationsquote2',
        scale=alt.Scale(zero=True)
    )
)

print(source['Migrationsquote2'].describe())
alt.vconcat(hist, box,).properties(title='Übersicht Migrationsquote2').configure_title(fon
```

```
count    1573.000000
mean       17.752142
std         9.628915
min         0.850662
25%        10.663616
50%        17.836257
75%        24.120116
max        53.982750
Name: Migrationsquote2, dtype: float64
```

```
alt.VConcatChart(...)
```

```python
hist = alt.Chart(source).mark_bar().encode(
    alt.X(
        "Christenquote",
        bin=True,
        scale=alt.Scale(zero=True)
    ),
    alt.Y('count()')
)
box = alt.Chart(source).mark_boxplot().encode(
    x=alt.X(
        'Christenquote',
        scale=alt.Scale(zero=True)
    )
)

print(source['Christenquote'].describe())
alt.vconcat(hist, box,).properties(title='Übersicht Christenquote').configure_title(fontSi
```

```
count    1573.000000
mean       62.137232
std        20.945943
min         5.933338
25%        58.604711
50%        68.010543
75%        75.942976
max        93.909239
Name: Christenquote, dtype: float64
```

```
alt.VConcatChart(...)
```

```python
hist = alt.Chart(source).mark_bar().encode(
    alt.X(
        "Männerquote",
        bin=True,
        scale=alt.Scale(zero=True)
    ),
    alt.Y('count()')
)
box = alt.Chart(source).mark_boxplot().encode(
    x=alt.X(
        'Männerquote',
        scale=alt.Scale(zero=True)
    )
)

print(source['Männerquote'].describe())
alt.vconcat(hist, box,).properties(title='Übersicht Männerquote').configure_title(fontSize
```

```
count    1573.000000
mean       48.697872
std         0.843340
min        45.102669
25%        48.190799
50%        48.702359
75%        49.177376
max        54.993659
Name: Männerquote, dtype: float64
```

```
alt.VConcatChart(...)
```

```python
hist = alt.Chart(source).mark_bar().encode(
    alt.X(
        "Akademikerquote",
        bin=True,
        scale=alt.Scale(zero=True)
    ),
    alt.Y('count()')
)
box = alt.Chart(source).mark_boxplot().encode(
    x=alt.X(
```

```
            'Akademikerquote',
            scale=alt.Scale(zero=True)
        )
)

print(source['Akademikerquote'].describe())
alt.vconcat(hist, box,).properties(title='Übersicht Akademikerquote').configure_title(font
```

```
count    1573.000000
mean       13.770178
std         5.853955
min         2.092871
25%         9.776536
50%        12.344777
75%        16.242999
max        47.997457
Name: Akademikerquote, dtype: float64
```

```
alt.VConcatChart(...)
```

```
hist = alt.Chart(source).mark_bar().encode(
    alt.X(
        "Beamtenquote",
        bin=True,
        scale=alt.Scale(zero=True)
    ),
    alt.Y('count()')
)
box = alt.Chart(source).mark_boxplot().encode(
    x=alt.X(
        'Beamtenquote',
        scale=alt.Scale(zero=True)
    )
)

print(source['Beamtenquote'].describe())
alt.vconcat(hist, box,).properties(title='Übersicht Beamtenquote').configure_title(fontSiz
```

```
count    1573.000000
```

```
mean        5.067968
std         1.740783
min         1.236476
25%         3.889789
50%         4.892966
75%         6.017192
max        18.870728
Name: Beamtenquote, dtype: float64
```

```
alt.VConcatChart(...)
```

```
hist = alt.Chart(source).mark_bar().encode(
    alt.X(
        "Singlequote",
        bin=True,
        scale=alt.Scale(zero=True)
    ),
    alt.Y('count()')
)
box = alt.Chart(source).mark_boxplot().encode(
    x=alt.X(
        'Singlequote',
        scale=alt.Scale(zero=True)
    )
)

print(source['Singlequote'].describe())
alt.vconcat(hist, box,).properties(title='Übersicht Singlequote').configure_title(fontSize
```

```
count    1573.000000
mean       52.214032
std         3.013940
min        44.397914
25%        50.252657
50%        51.690254
75%        53.661406
max        66.462950
Name: Singlequote, dtype: float64
```

```
alt.VConcatChart(...)
```

1.5.2 Exploratory data analysis

1.5.3 Relationships

```
alt.Chart(source, width=200, height=150).mark_circle(size=60).encode(
    alt.X(
        alt.repeat("repeat"),
        type="quantitative",
        scale=alt.Scale(zero=False)),
    alt.Y('Arbeitslosenquote2'),
    tooltip = ['Name',alt.Tooltip(alt.repeat("repeat"), type="quantitative"), alt.Y('Arbei
).repeat(
    repeat=predictor,
    columns=4
).interactive()
```

```
alt.RepeatChart(...)
```

```
alt.Chart(source).mark_circle(size=60).encode(
    x=alt.X('Migrationsquote2'),
    y=alt.Y('Arbeitslosenquote2',
            title='ALO_Quote'),
    tooltip=['Migrationsquote2', 'Arbeitslosenquote2','Name']
).interactive()
```

```
alt.Chart(...)
```

```
corr_data = source[['Migrationsquote2','Arbeitslosenquote2']]
corr = corr_data.corr(method='pearson').round(5)
corr
```

	Migrationsquote2	Arbeitslosenquote2
Migrationsquote2	1.00000	-0.27309
Arbeitslosenquote2	-0.27309	1.00000

```python
corr_blues = corr.style.background_gradient(cmap='Blues')
corr_blues
```

Table 12

	Migrationsquote2	Arbeitslosenquote2
Migrationsquote2	1.000000	-0.273090
Arbeitslosenquote2	-0.273090	1.000000

```python
corr_list = corr['Arbeitslosenquote2'].sort_values(ascending=False)
corr_list
```

```
Arbeitslosenquote2    1.00000
Migrationsquote2     -0.27309
Name: Arbeitslosenquote2, dtype: float64
```

```python
# inspect correlation between outcome and possible predictors
corr = df_train.corr(method = 'pearson').round(5)
corr[y_label].sort_values(ascending=False)
```

```
Arbeitslosenquote2    1.00000
Singlequote           0.44441
Akademikerquote      -0.10260
Männerquote          -0.23303
Beamtenquote         -0.25672
Migrationsquote2     -0.29545
Christenquote        -0.66274
Name: Arbeitslosenquote2, dtype: float64
```

```python
# take a look at all correlations
corr.style.background_gradient(cmap='Blues')
```

Table 13

	Migrationsquote2	Christenquote	Männerquote	Akademikerquote	Beamtenquote
Migrationsquote2	1.000000	0.430310	-0.049660	0.093810	-0.014510
Christenquote	0.430310	1.000000	0.153050	-0.253270	0.286860
Männerquote	-0.049660	0.153050	1.000000	-0.303060	-0.091700
Akademikerquote	0.093810	-0.253270	-0.303060	1.000000	0.273150
Beamtenquote	-0.014510	0.286860	-0.091700	0.273150	1.000000
Singlequote	0.063220	-0.315040	-0.274020	0.239260	-0.039460
Arbeitslosenquote2	-0.295450	-0.662740	-0.233030	-0.102600	-0.256720

1.6 Model

1.6.1 Select model

```
data = df_analyse_gemeinde.dropna()[['Name','Migrationsquote2', 'Arbeitslosenquote2']]
data
```

	Name	Migrationsquote2	Arbeitslosenquote2
0	Flensburg, Stadt	15.957447	6.657547
1	Kiel, Landeshauptstadt	18.900021	7.539341
2	Lübeck, Hansestadt	16.812500	7.167394
3	Neumünster, Stadt	16.924489	6.899185
4	Brunsbüttel, Stadt	13.682565	5.365854
...	...	...	...
1568	Greiz, Stadt	2.112338	6.813820
1569	Zeulenroda-Triebes, Stadt	3.613666	5.662651
1570	Altenburg, Stadt	1.978736	9.632751
1571	Meuselwitz, Stadt	2.098540	9.363958
1572	Schmölln, Stadt	3.710095	6.430868

```
data.describe()
```

	Migrationsquote2	Arbeitslosenquote2
count	1573.000000	1573.000000
mean	17.752142	4.225062
std	9.628915	2.100031
min	0.850662	0.780031

	Migrationsquote2	Arbeitslosenquote2
25%	10.663616	2.796174
50%	17.836257	3.619303
75%	24.120116	5.022500
max	53.982750	16.871705

```
y_label = "Arbeitslosenquote2"

X = data[["Migrationsquote2"]]
y = data[y_label]
```

```
# Choose the linear regression model
reg_test = LinearRegression()
```

```
# Fit the model to the data
reg_test.fit(X, y)
```

```
LinearRegression()
```

```
print(f' Intercept: {reg_test.intercept_:.4} \n Slope: {reg_test.coef_[0]:.3}')
```

```
 Intercept: 5.282
 Slope: -0.0596
```

```
# Intercept
reg_test.intercept_
```

```
5.282378184546983
```

```
# Slope
reg_test.coef_
```

```
array([-0.0595599])
```

```python
# Make predictions on the data
y_pred = reg_test.predict(X)
y_pred
```

```
array([4.33195426, 4.15669481, 4.28102737, ..., 5.16452487, 5.15738934,
       5.0614053 ])
```

```python
mean_squared_error(y, y_pred)
```

```
4.078635290942068
```

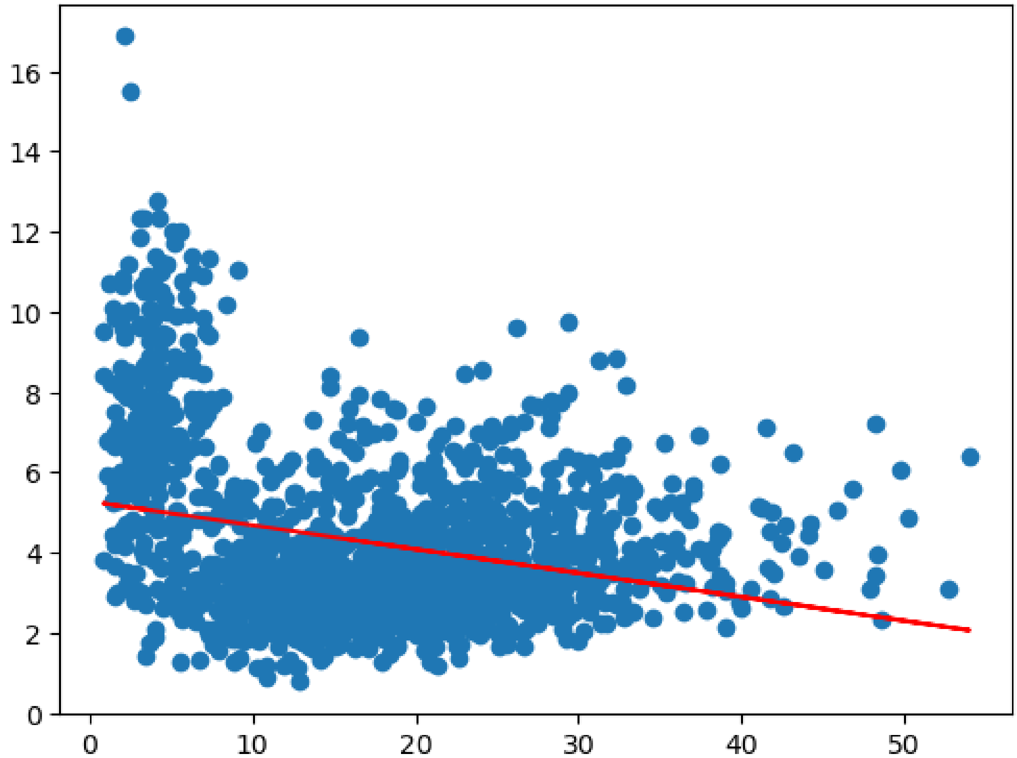
```python
mean_squared_error(y, y_pred, squared=False)
```

```
2.0195631435887487
```

```python
x_Scatter =  data['Migrationsquote2']
y_Scatter = data['Arbeitslosenquote2']

X = data[["Migrationsquote2"]]
y_pred = y_pred

plt.scatter(x_Scatter, y_Scatter)
plt.plot(X, y_pred, color='red')
plt.show()
```




```
reg_mig = LinearRegression()
reg_chr = LinearRegression()
reg_sin = LinearRegression()
reg_multi=LinearRegression()
```

1.6.2 Select Model Lasso

```
X_train_lasso = X_train.copy()
X_test_lasso = X_test.copy()
scaler = StandardScaler().fit(X_train[features])

X_train_lasso[features] = scaler.transform(X_train_lasso[features])
X_test_lasso[features] = scaler.transform(X_test_lasso[features])
```

```
X_train
```

	Migrationsquote2	Christenquote	Männerquote	Akademikerquote	Beamtenquote	Singlequote
1041	29.206142	73.971140	48.100815	18.275467	5.090006	53.898667
277	18.195158	80.491887	49.356036	10.834050	4.965517	52.041039
1223	33.358298	67.257531	47.849582	16.443128	3.807391	55.075046
925	21.221751	75.438658	48.500299	16.352459	5.246523	50.564366
1161	25.235602	85.163236	49.448950	10.391198	5.534351	50.207943
...	...	...	...	...	...	...
1130	19.279854	60.266185	46.379427	30.991957	5.922747	53.891270
1294	12.534626	81.905846	49.614947	12.569170	6.327373	51.597134
860	19.919110	65.085772	48.678103	16.607774	4.291045	50.232089
1459	4.362730	14.812994	48.360429	13.388544	2.231237	52.158948
1126	27.406765	67.395069	49.459883	18.365288	5.927052	59.627278

```
# select the lasso model with built in crossvalidation
reg = LassoCV(cv=5, random_state=0)
```

1.6.3 Training and validation

```
# cross-validation with 5 folds
scores_mig = cross_val_score(reg_mig, X_train[['Migrationsquote2']], y_train, cv=5, scorin
scores_chr = cross_val_score(reg_chr, X_train[['Christenquote']], y_train, cv=5, scoring='
scores_sin = cross_val_score(reg_sin, X_train[['Singlequote']], y_train, cv=5, scoring='ne
# cross-validation with 5 folds total
scores = cross_val_score(reg_multi, X_train, y_train, cv=5, scoring='neg_mean_squared_erro
```

```
# store cross-validation scores: Migrationsquote, Christenquote und Singlequote
df_scores_mig = pd.DataFrame({"lr": scores_mig})
df_scores_chr = pd.DataFrame({"lr": scores_chr})
df_scores_sin = pd.DataFrame({"lr": scores_sin})

# reset index to match the number of folds
df_scores_mig.index += 1
df_scores_chr.index += 1
df_scores_sin.index += 1

# print dataframe

df_scores_mig.style.background_gradient(cmap='Blues')
```

Table 17

	lr
1	3.914431
2	3.731555
3	3.467859
4	4.145899
5	4.440537

```
#Christenquote
df_scores_chr.style.background_gradient(cmap='Blues')
```

Table 18

	lr
1	2.060155
2	2.423749
3	2.352862
4	2.447104
5	2.804205

```
#Singlequote
df_scores_sin.style.background_gradient(cmap='Blues')
```

Table 19

	lr
1	3.449375
2	3.092362
3	2.863533
4	3.594474
5	4.297317

```
# store cross-validation scores Multiple Regression
df_scores = pd.DataFrame({"lr": scores})

# reset index to match the number of folds Multiple Regression
df_scores.index += 1
```

```
# print dataframe
df_scores.style.background_gradient(cmap='Blues')
```

Table 20

	lr
1	1.443932
2	1.526375
3	1.385411
4	1.527816
5	2.038018

Chart Folds Migrationsquote

```
alt.Chart(df_scores_mig.reset_index()).mark_line(
     point=alt.OverlayMarkDef()
).encode(
    x=alt.X("index", bin=False, title="Fold", axis=alt.Axis(tickCount=5)),
    y=alt.Y("lr", aggregate="mean", title="Mean squared error (MSE)")
)
```

```
alt.Chart(...)
```

Chart Folds Christenquote

```
alt.Chart(df_scores_chr.reset_index()).mark_line(
     point=alt.OverlayMarkDef()
).encode(
    x=alt.X("index", bin=False, title="Fold", axis=alt.Axis(tickCount=5)),
    y=alt.Y("lr", aggregate="mean", title="Mean squared error (MSE)")
)
```

```
alt.Chart(...)
```

Chart Folds Singlequote

```
alt.Chart(df_scores_sin.reset_index()).mark_line(
     point=alt.OverlayMarkDef()
).encode(
    x=alt.X("index", bin=False, title="Fold", axis=alt.Axis(tickCount=5)),
    y=alt.Y("lr", aggregate="mean", title="Mean squared error (MSE)")
)
```

```
alt.Chart(...)
```

Chart Folds Multiple Regression

```
alt.Chart(df_scores.reset_index()).mark_line(
     point=alt.OverlayMarkDef()
).encode(
    x=alt.X("index", bin=False, title="Fold", axis=alt.Axis(tickCount=5)),
    y=alt.Y("lr", aggregate="mean", title="Mean squared error (MSE)")
)
```

```
alt.Chart(...)
```

```
df_scores_mig.describe().T
```

	count	mean	std	min	25%	50%	75%	max
lr	5.0	3.940056	0.37415	3.467859	3.731555	3.914431	4.145899	4.440537

```
df_scores_chr.describe().T
```

	count	mean	std	min	25%	50%	75%	max
lr	5.0	2.417615	0.265673	2.060155	2.352862	2.423749	2.447104	2.804205

```
df_scores_sin.describe().T
```

	count	mean	std	min	25%	50%	75%	max
lr	5.0	3.459412	0.550051	2.863533	3.092362	3.449375	3.594474	4.297317

```
df_scores.describe().T
```

	count	mean	std	min	25%	50%	75%	max
lr	5.0	1.584311	0.260608	1.385411	1.443932	1.526375	1.527816	2.038018

1.6.4 Training & Best Alpha Lasso Regression

```
reg.fit(X_train_lasso, y_train)
```

```
LassoCV(cv=5, random_state=0)
```

```
reg.alpha_
```

```
0.0063775417634839085
```

1.6.5 Fit model

```
# Fit the model to the complete training data
reg_mig.fit(X_train[['Migrationsquote2']], y_train)
reg_chr.fit(X_train[['Christenquote']], y_train)
reg_sin.fit(X_train[['Singlequote']], y_train)
```

```
LinearRegression()
```

```
# Fit the model to the complete training data
reg_multi.fit(X_train, y_train)
```

```
LinearRegression()
```

Migrationsquote

```
# intercept
intercept = pd.DataFrame({
    "Name": ["Intercept"],
    "Coefficient":[reg_mig.intercept_]}
    )

# make a slope table
slope = pd.DataFrame({
    "Name": 'slope',
    "Coefficient": reg_mig.coef_}
)

# combine estimates of intercept and slope
table = pd.concat([intercept, slope], ignore_index=True, sort=False)

round(table, 3)
```

	Name	Coefficient
0	Intercept	5.342
1	slope	-0.064

Christenquote

```
# intercept
intercept = pd.DataFrame({
    "Name": ["Intercept"],
    "Coefficient":[reg_chr.intercept_]}
    )

# make a slope table
slope = pd.DataFrame({
    "Name": 'slope',
    "Coefficient": reg_chr.coef_}
)

# combine estimates of intercept and slope
table = pd.concat([intercept, slope], ignore_index=True, sort=False)

round(table, 3)
```

	Name	Coefficient
0	Intercept	8.241
1	slope	-0.065

Singlequote

```
# intercept
intercept = pd.DataFrame({
    "Name": ["Intercept"],
    "Coefficient":[reg_sin.intercept_]}
    )

# make a slope table
slope = pd.DataFrame({
    "Name": 'slope',
    "Coefficient": reg_sin.coef_}
)

# combine estimates of intercept and slope
table = pd.concat([intercept, slope], ignore_index=True, sort=False)

round(table, 3)
```

	Name	Coefficient
0	Intercept	-12.168
1	slope	0.314

Multiple Regression

```
# intercept
intercept = pd.DataFrame({
    "Name": ["Intercept"],
    "Coefficient":[reg_multi.intercept_]}
    )

# make a slope table
slope = pd.DataFrame({
    "Name": features,
    "Coefficient": reg_multi.coef_}
)
```

```
# combine estimates of intercept and slopes
table = pd.concat([intercept, slope], ignore_index=True, sort=False)

round(table, 3)
```

	Name	Coefficient
0	Intercept	20.239
1	Migrationsquote2	-0.000
2	Christenquote	-0.064
3	Männerquote	-0.428
4	Akademikerquote	-0.147
5	Beamtenquote	0.044
6	Singlequote	0.203

1.6.6 Fit Model Lasso Regression

```
# Fit the model to the complete training data
reg = Lasso(alpha=reg.alpha_)
reg.fit(X_train_lasso, y_train)
```

```
Lasso(alpha=0.0063775417634839085)
```

```
# intercept
intercept = pd.DataFrame({
    "Name": ["Intercept"],
    "Coefficient":[reg.intercept_]}
    )

# make a slope table
slope = pd.DataFrame({
    "Name": features,
    "Coefficient": reg.coef_}
)

# combine estimates of intercept and slopes
table = pd.concat([intercept, slope], ignore_index=True, sort=False)
```

```python
round(table, 3)
```

	Name	Coefficient
0	Intercept	4.215
1	Migrationsquote2	-0.003
2	Christenquote	-1.350
3	Männerquote	-0.349
4	Akademikerquote	-0.812
5	Beamtenquote	0.062
6	Singlequote	0.591

1.6.7 Evaluation on test set

```python
# obtain predictions
y_pred_mig = reg_mig.predict(X_test[['Migrationsquote2']])
y_pred_chr = reg_chr.predict(X_test[['Christenquote']])
y_pred_sin = reg_sin.predict(X_test[['Singlequote']])
y_pred_multi = reg_multi.predict(X_test)
```

```python
test = pd.DataFrame(
    {"a": [15, 30, 20]}
)
test
```

	a
0	15
1	30
2	20

```python
reg_mig.predict(test)
```

```
array([4.3892813 , 3.43630654, 4.07162304])
```

```python
X_test[['Migrationsquote2']]
```

	Migrationsquote2
1120	18.461538
810	15.162791
1339	3.671189
534	18.630933
514	14.435390
...	...
1263	21.283255
1281	10.962963
1209	12.860013
1007	22.473868
1404	5.213904

```
# R squared Migrationsquote
r2_score(y_test, y_pred_mig).round(3)
```

```
0.027
```

```
# R squared Christenquote
r2_score(y_test, y_pred_chr).round(3)
```

```
0.382
```

```
# R squared Singlequote
r2_score(y_test, y_pred_sin).round(3)
```

```
0.121
```

```
# R squared Multiple Regressio
r2_score(y_test, y_pred_multi).round(3)
```

```
0.636
```

```
#adjusted R squared Migrationsquote- gem. Buch Chapter 8
print((1-(1-r2_score(y_test, y_pred_mig))*((len(X_test[['Migrationsquote2']])-1)/(len(X_te
```

0.024

```
#adjusted R squared Christenquote- gem. Buch Chapter 8
print((1-(1-r2_score(y_test, y_pred_chr))*((len(X_test[['Christenquote']])-1)/(len(X_test[
```

0.38

```
#adjusted R squared Singlequote- gem. Buch Chapter 8
print((1-(1-r2_score(y_test, y_pred_sin))*((len(X_test[['Singlequote']])-1)/(len(X_test[['
```

0.118

```
#adjusted R squared Multiple Regression - gem. Buch Chapter 8
print((1-(1-r2_score(y_test, y_pred_multi))*((len(X_test)-1)/(len(X_test)-len(X_test.colum
```

0.629

```
# MSE Migrationsquote
mean_squared_error(y_test, y_pred_mig).round(3)
```

4.708

```
# MSE Christenquote
mean_squared_error(y_test, y_pred_chr).round(3)
```

2.991

```
# MSE Singlequote
mean_squared_error(y_test, y_pred_sin).round(3)
```

4.254

```python
# MSE Multiple Regression
mean_squared_error(y_test, y_pred_multi).round(3)
```

1.762

```python
# RMSE Migrationsquote
mean_squared_error(y_test, y_pred_mig, squared=False).round(3)
```

2.17

```python
# RMSE Christenquote
mean_squared_error(y_test, y_pred_chr, squared=False).round(3)
```

1.729

```python
# RMSE Singlequote
mean_squared_error(y_test, y_pred_sin, squared=False).round(3)
```

2.063

```python
# RMSE Multiple Regression
mean_squared_error(y_test, y_pred_multi, squared=False).round(3)
```

1.327

```python
# MAE Migrationsquote
mean_absolute_error(y_test, y_pred_mig).round(3)
```

1.686

```python
# MAE Christenquote
mean_absolute_error(y_test, y_pred_chr).round(3)
```

1.296

```
# MAE Singlequote
mean_absolute_error(y_test, y_pred_sin).round(3)
```

```
1.492
```

```
# MAE Multiple Regression
mean_absolute_error(y_test, y_pred_multi).round(3)
```

```
1.004
```

1.6.8 Evaluation on test set Lasso Regression

```
# obtain predictions
y_pred_lasso = reg.predict(X_test_lasso)
```

```
# R squared
r2_score(y_test, y_pred_lasso).round(3)
```

```
0.635
```

```
#adjusted R squared - gem. Buch Chapter 8
print((1-(1-r2_score(y_test, y_pred_lasso))*((len(X_test_lasso)-1)/(len(X_test_lasso)-len(
```

```
0.628
```

```
# MSE
mean_squared_error(y_test, y_pred_lasso).round(3)
```

```
1.767
```

```
# RMSE
mean_squared_error(y_test, y_pred_lasso, squared=False).round(3)
```

```
1.329
```

```python
# MAE
mean_absolute_error(y_test, y_pred_lasso).round(3)
```

```
1.004
```

1.6.9 Feature Importance Multiple Regression

```python
importance = np.abs(reg_multi.coef_)

df_imp = pd.DataFrame({"coeff": importance,
                       "name": features}).round(3)
df_imp
```

	coeff	name
0	0.000	Migrationsquote2
1	0.064	Christenquote
2	0.428	Männerquote
3	0.147	Akademikerquote
4	0.044	Beamtenquote
5	0.203	Singlequote

```python
alt.Chart(df_imp).mark_bar().encode(
    x="coeff",
    y=alt.Y("name", sort='-x')
)
```

```
alt.Chart(...)
```

1.6.10 Feature Importance Lasso

```python
importance = np.abs(reg.coef_)

df_imp = pd.DataFrame({"coeff": importance,
                       "name": features}).round(3)
df_imp
```

	coeff	name
0	0.003	Migrationsquote2
1	1.350	Christenquote
2	0.349	Männerquote
3	0.812	Akademikerquote
4	0.062	Beamtenquote
5	0.591	Singlequote

```
alt.Chart(df_imp).mark_bar().encode(
    x="coeff",
    y=alt.Y("name", sort='-x')
)
```

```
alt.Chart(...)
```

1.6.11 Save model

Save your model in the folder `models/`. Use a meaningful name and a timestamp.

```
TIME = "-" + time.strftime("%Y%m%d-%H%M")
PATH = "../models/"
FILE_CHR = "reg_model_linreg_christenquote"
FILE_MUL = "reg_model_multiplereg"
FILE_LAS = "reg_model_lassoreg"
FORMAT = ".pkl"
```

```
joblib.dump(reg_chr, PATH + FILE_CHR + TIME + FORMAT)
joblib.dump(reg_multi, PATH + FILE_MUL + TIME + FORMAT)
joblib.dump(reg, PATH + FILE_LAS + TIME + FORMAT)
```

```
['../models/reg_model_lassoreg-20230108-2149.pkl']
```

```
final_model_linreg = joblib.load(PATH + FILE_CHR + TIME + FORMAT)
final_model_multireg = joblib.load(PATH + FILE_MUL + TIME + FORMAT)

# pretend this is new data (3 observations)
new_data_linreg = X[['Migrationsquote2']].iloc[:3]
```

```python
new_data =  X.iloc[:3]

# make predictions for the three observations
predictions_linreg = final_model_linreg.predict(new_data_linreg)
predictions_multireg = final_model_multireg.predict(new_data)
```

```
ValueError: X has 1 features, but LinearRegression is expecting 6 features as input.
```

```python
predictions_linreg
```

```python
predictions_multireg
```

1.7 Conclusions

Um ein Verständnis für die Daten zu erhalten, beschreiben wir zuerst unsere bereinigte Datengrundlage, welche für die Anwendung der Modelle genutzt wird.

```python
alt.Chart(df_analyse_gemeinde, width=200, height=150).mark_bar().encode(
    alt.X(alt.repeat("repeat"), type="quantitative", bin=True),
    y='count()'
).repeat(
    repeat=Quoten,
    columns=3
)
```

```
alt.RepeatChart(...)
```

Das Histogramm "Christenquote" weist eine linksschiefe, multimodale Verteilung auf. Die "Männerquote" weist eine annähernd symetrische, unimodale Verteilung auf. Alle weiteren Variablen sind rechtsschief, unimodal verteilt.

```python
# take a look at all correlations
corr.style.background_gradient(cmap='Blues')
```

Table 34

	Migrationsquote2	Christenquote	Männerquote	Akademikerquote	Beamtenquote	S
Migrationsquote2	1.000000	0.430310	-0.049660	0.093810	-0.014510	0
Christenquote	0.430310	1.000000	0.153050	-0.253270	0.286860	-
Männerquote	-0.049660	0.153050	1.000000	-0.303060	-0.091700	-
Akademikerquote	0.093810	-0.253270	-0.303060	1.000000	0.273150	0
Beamtenquote	-0.014510	0.286860	-0.091700	0.273150	1.000000	-
Singlequote	0.063220	-0.315040	-0.274020	0.239260	-0.039460	1
Arbeitslosenquote2	-0.295450	-0.662740	-0.233030	-0.102600	-0.256720	0

Die stärkste positive Korrelation, in dem untersuchten df_analyse_Gemeinde, zwischen Arbeitslosenquote und den Predictor Variables weist die Singlequote, mit r = +0.44441, auf. Die stärkste negative Korrelation mit der Arbeitslosenquote weist die Christenquote, mit r = -0.66274, auf. Die geringste Korrelation weist die "Akademikerquote", mit r = -0.102600, auf.

```
alt.Chart(source, width=200, height=150).mark_circle(size=60).encode(
    alt.X(
        alt.repeat("repeat"),
        type="quantitative",
        scale=alt.Scale(zero=False)),
    alt.Y('Arbeitslosenquote2'),
    tooltip = ['Name',alt.Tooltip(alt.repeat("repeat"), type="quantitative"), alt.Y('Arbei
).repeat(
    repeat=predictor,
    columns=4
).interactive()
```

```
alt.RepeatChart(...)
```

1.8 Conclusion Models

1.8.1 Lineare Regression

Folgende Statistiken wurden mit der lineraren Regression für die folgenden Quoten ermittelt:

```
lin_reg_overview = pd.DataFrame(
    {'Statistik' : [
        'R squared',
```

```
        'R squared adj.',
        'MSE',
        'RMSE',
        'MAE'
    ],
    'Migrationsquote' : [
        '0.027',
        '0.024',
        '4.708',
        '2.17',
        '1.686'
    ],
    'Christenquote' : [
        '0.382',
        '0.38',
        '2.991',
        '1.729',
        '1.296'
    ],
    'Singlequote' : [
        '0.121',
        '0.118',
        '4.254',
        '2.063',
        '1.492'
    ]
        }
)
lin_reg_overview
```

	Statistik	Migrationsquote	Christenquote	Singlequote
0	R squared	0.027	0.382	0.121
1	R squared adj.	0.024	0.38	0.118
2	MSE	4.708	2.991	4.254
3	RMSE	2.17	1.729	2.063
4	MAE	1.686	1.296	1.492

Von diesen drei Modellen ist das Modell mit der Christenquote als Prädikator noch am Besten. Mit dem R squared zeigt sich trotzdem eine mäßige Güte des Models. Nur 38.2% der Variabilität der Arbeitslosigkeit wird hiermit erklärt.

1.8.2 Multiple Regression

Der R squared beträgt 0.636 und bedeutet eine mittlere Güte des Modells. Etwa 63.6 % der Variabilität der Arbeitslosigkeit wird durch die multiple Regression erklärt. Der adjusted R squared beträgt 0.629 und erklärt 62.9 % der Variabilität der Arbeitslosigkeit. Somit ist der adjusted R squared minimal schlechter als der R squared Wert.

Der mean sqaured error (1.762), root mean squared error (1.327) und der mean absolute error (1.004) ist niedriger als bei den Modellen der linearen Regression. Aus diesem Grund ist die multiple Regression der linearen Regression vorzuziehen.

1.8.3 Lasso Regression

Der R squared beträgt 0.635 und bedeutet eine mittlere Güte des Modells. Etwa 63.5 % der Variabilität der Arbeitslosigkeit wird durch die Lasso Regression erklärt. Der adjusted R squared beträgt 0.628 und erklärt 62.7 % der Variabilität der Arbeitslosigkeit. Somit ist der adjusted R squared minimal schlechter als der R squared Wert.

Der mean sqaured error (1.767), root mean squared error (1.329) und der mean absolute error (1.004) ist minimal niedriger als bei der multiplen Regression. Aus diesem Grund ist unterscheiden sich die Lasso und multiple Regression kaum.