DataPreprocessingMilestone2

June 28, 2020

1 Applied Machine Intelligence - Group 10

1.0.1 Data Preprocessing

This notebook takes in data on greenhouse gas emissions and its indicators and preprocess them for later use. It was created using Google Colab.

All preprocessed files will be stored in a container called `database` and exported as a JSON file. Inside the container we have the following elements: `sector`, `category`, `yearly_data` and `data`. `data` is a Pandas DataFrame for one feature with timestamps and values.

The JSON file will then be the input for all further steps of the data proccesing pipeline.

In [1]:
```
# Import necessary packages
import numpy as np
import pandas as pd
import seaborn as sns
import json
import datetime
import matplotlib.pyplot as plt
```

In [2]:
```
# Create database
database = {}
```

In [3]:
```
# Plotting function
# ticks_spacing: specify the distance between the x ticks (default 1)
# max_ticks: specify the maximum number of x ticks (defaul 31)
def plot_data(timeseries, feature_name, ticks_spacing = 1, max_ticks = 31):

  x_values = timeseries.index
  y_values = timeseries.iloc[:,0]

  plt.figure(figsize=(18, 6))
  ax = sns.pointplot(x=x_values, y=y_values)
  plt.xticks(rotation=90)
  plt.xlabel('time scope')
  plt.title('Plot feature: ' + feature_name)
  plt.grid()

  #change xticks labels
```

```
if ticks_spacing != 1:
  ticks = ax.get_xticklabels()
  for label in ax.get_xticklabels()[::1]:
      label.set_visible(False)
  for label in ticks[::ticks_spacing]:
      label.set_visible(True)
else:
  if len(x_values) > max_ticks:
      ticks_spacing = int(len(x_values)/max_ticks)
  ticks = ax.get_xticklabels()
  for label in ax.get_xticklabels()[::1]:
      label.set_visible(False)
  for label in ticks[::ticks_spacing]:
      label.set_visible(True)

plt.show()
```

2 Mobility

2.1 Vehicle traffic

Different data sources are taken into account and proposed to help modeling the CO2 emissions of the vehicle traffic sector. How this data is proposed to be merged is explained step by step in the regarding data sections.

2.1.1 BAST Traffic Count data Germany

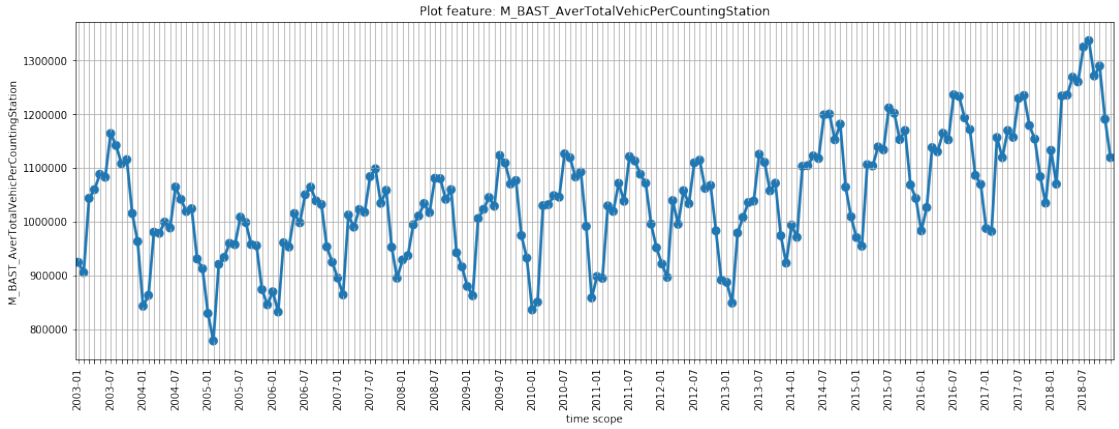
Overview of the data:
Timespan: 2003 until 2018
Frequency: monthly
Number of samples: 192
Features: 1

Why did we choose the data source and how it might help us:
Bundesanstalt für StraSSenwesen (BAST) collects the data of the traffic count stations of the individual states (Bundesländer) and summarizes it in one central database. These traffic count data represent the traffic utilization in Germany and mostly covers the street type A and B.
Following link leads to a map that shows Germany with the marked BAST stations. It can be seen that the stations are well distrubuted over the area of Germany. Map BAST stations Germany
The dataset well covers the traffic development of whole Germany in a time series. Seasonal development of one year but also of the year to year timeseries can be extracted and used as an indicator to model the traffic related greenhouse gas emissions of Germany.

Dataprocessing notebook: M_BuildBASTDataset.ipynb
The hourly data of all stations is downloaded by a webcrawler and processed to daily and monthly sums of each traffic count station. This value represents the total number of vehicles passing the counting station in that month. Of all available stations in one month the average is taken which represents the average total number of vehicles per traffic counting station in the corresponding month. This value is independent by the number of counting stations and therefore enables a comparable timeseries.

Limitations:
Data is only available until 2018 and only for street type A and B. Therefore it does not directly covers urban areas.

```
In [4]: # Load your data (specify file path - upload your file first)
        df = pd.read_csv('../data/mobility/BAST_CountingStations_Feature_monthly.csv')
        # Add to database
        columns = list(df)
        columns.pop(0)
        # The for loop is only necessary if you have multiple features in the same CSV
        for i in columns:
                database[i] = {}
                database[i]['sector'] = 'mobility'
                database[i]['category'] = 'traffic'
                database[i]['yearly_data'] = False

                # Create Pandas DataFrame for single feature
                timeseries=df['date'].to_frame().join(df[i])
                timeseries = timeseries.set_index('date')
                #timeseries.date = pd.to_datetime(df.date).dt.to_period('m')
                # Convert dataframe to JSON format
                database[i]['data'] = timeseries.to_json()

                plot_data(timeseries, i)
```



2.1.2 BAYSIS Traffic Count data

Overview of the data:
Timespan: February 2017 until April 2020
Number of samples: 39
Features: 1

Why did we choose the data source and how it might help us:
The traffic count stations of BAYSIS (Bayerisches Staatsministerium für Wohnen, Bau und Verkehr)

are also included in the BAST traffic count database, but much more recent data is available on the BAYSIS website. But the BAYSIS data back to 2003 can be extracted from the BAST dataset which is explained in the next section.
Following link leads to a map which show the gridded traffic counting stations in Bavaria Map BASIS stations Germany. With the resent data of Bavaria the traffic of whole Germany can be modeled. How this is proposed is also covered in the next section "BAST traffic count data for Bavaria".

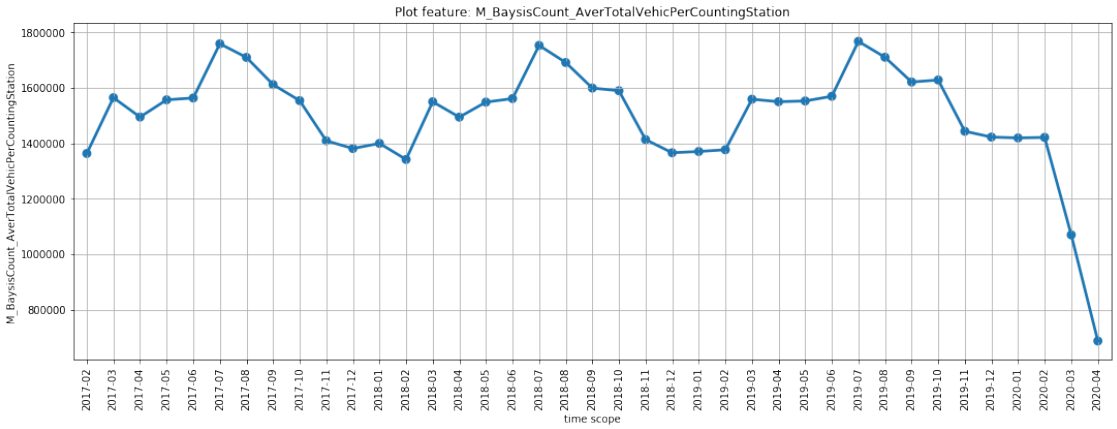
Dataprocessing notebook: M_ProcessBaysisData.ipynb

The data is available in daily averages of vehicles passing the counting station for each month. These values are weighted by the number of days of the corresponding month to get the total number of the vehicles passing the station in that month. Of all available traffic count stations in one month the average is taken which represents the average total number of vehicles per traffic counting station in the corresponding month. This value is independent by the number of counting stations and should extend the timespan of the BAST traffic count dataset.

Limitations:

Start of data availability is 2017. Before that date only yearly data and quarter yearly data is available. The dataset only represents traffic count data for the stations in Bavaria.

```
In [5]: # Load your data (specify file path - upload your file first)
        df = pd.read_csv('../data/mobility/Baysis_CountingStations_Feature_monthly.csv')
        # Add to database
        columns = list(df)
        columns.pop(0)
        # The for loop is only necessary if you have multiple features in the same CSV
        for i in columns:
                database[i] = {}
                database[i]['sector'] = 'mobility'
                database[i]['category'] = 'traffic'
                database[i]['yearly_data'] = False

                # Create Pandas DataFrame for single feature
                timeseries=df['date'].to_frame().join(df[i])
                timeseries = timeseries.set_index('date')
                # Convert dataframe to JSON format
                database[i]['data'] = timeseries.to_json()

                plot_data(timeseries, i, ticks_spacing = 1)
```



2.1.3 BAST Traffic Count data Bavaria

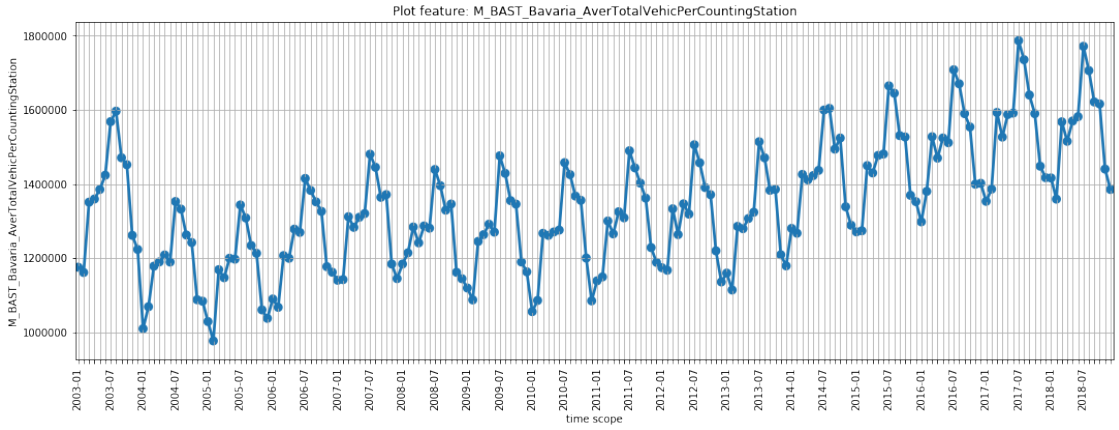
Overview of the data:
Timespan: 2003 until 2018
Frequency: monthly
Number of samples: 192
Features: 1

Why did we choose the data source and how it might help us:
Bundesanstalt für StraSSenwesen (BAST) collects the data of the traffic count stations of the individual states (Bundesländer) and summarizes them in one central database. These traffic count data represent the traffic utilization in Germany and mostly covers the street type A and B. It is only available until the year 2018 but data for Bavaria is available until April 2020 (BAYSIS dataset). As the bavarian stations are included in the BAST dataset they can be extracted and therefor the BAYSIS dataset, which only covers monthly values back to 2017, can be extended back to the year 2003. The relation of the traffic in Bavaria and the traffic in Germany for the years 2003 until 2018, which both datasets cover, can be used to model the traffic of Germany only using the traffic of Bavaria from the BAYSIS dataset. Following figure shows a scatter plot of the average total number of vehicles per traffic counting station in the corresponding month for Germany and Bavaria Scatter plot. A very linear relationship between bavarian and german traffic can be seen and therefore it is possible to calculate german traffic based on bavarian traffic. For the time during the Corona lockdown the following mobility reports have to be used, because the relation between Bavarian and German traffic may differ, due to different regulations in the individual states.

Dataprocessing notebook: M_ExtractBavariaFromBAST.ipynb
The bavarian stations are extracted of the BAST dataset by identifying their station numbers with the BAYSIS dataset. Of all available stations in one month the average is taken which represents the average total number of vehicles per traffic counting station in the corresponding month. This value is independent by the number of counting stations and therefore enables a comparable time-series.

Limitations:
Data is only avialable until 2018 and only for street type A and B and therefor not directly covers urban areas.

```
In [6]: # Load your data (specify file path - upload your file first)
        df = pd.read_csv('../data/mobility/BAST_Bavaria_CountingStations_Feature_monthly.csv')
        # Add to database
        columns = list(df)
        columns.pop(0)
        # The for loop is only necessary if you have multiple features in the same CSV
        for i in columns:
                database[i] = {}
                database[i]['sector'] = 'mobility'
                database[i]['category'] = 'traffic'
                database[i]['yearly_data'] = False

                # Create Pandas DataFrame for single feature
                timeseries=df['date'].to_frame().join(df[i])
                timeseries = timeseries.set_index('date')
                # Convert dataframe to JSON format
                database[i]['data'] = timeseries.to_json()

                plot_data(timeseries, i, ticks_spacing = 1)
```



2.1.4 Mileage in km

Overview of the data:
Timespan: 2014 until 2018
Number of samples: 4
Features: 3

Why did we choose the data source and how it might help us:
The dataset contains information of the domestic mileage for the years 2014 until 2018. The data is collected at the general car inspection in Germany. It is divided in e.g. vehicle types, fuel type and similar. With mileage it is possible to estimate an approximately greenhouse gas emission for the corresponding year via the buttom up estimation.

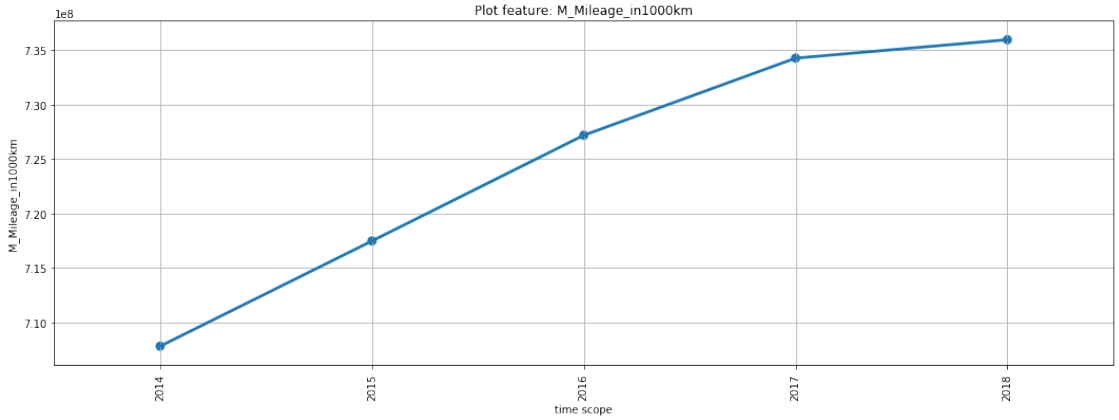
Dataprocessing notebook: M_Process_TrafficInKM.ipynb
The data is downloaded and processed to the csv format. It contains yearly values and only the

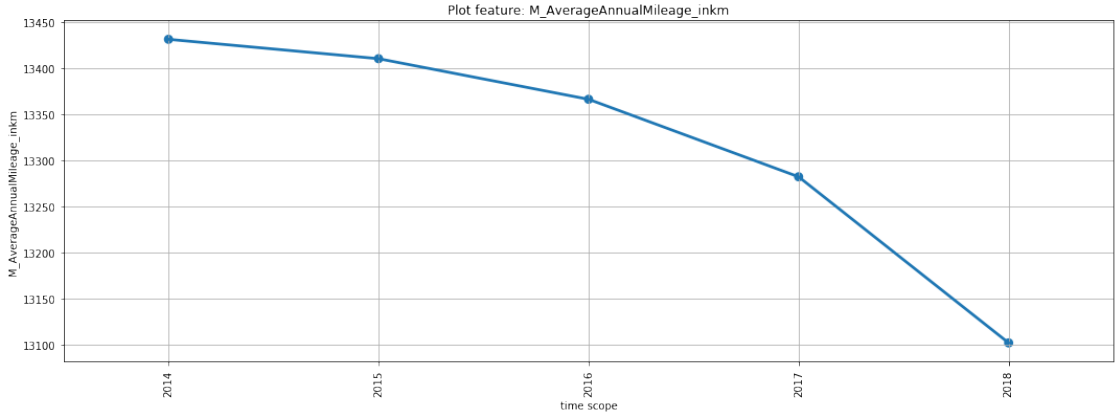
total mileage (without any separation in vehicle types or similar) is taken and stored in the feature value M_Mileage_in1000km. The feature M_AverageAnnualMileage_inkm contains information about the annual average mileage per vehicle and M_MediumVehicleInvetory covers the vehicle inventory.

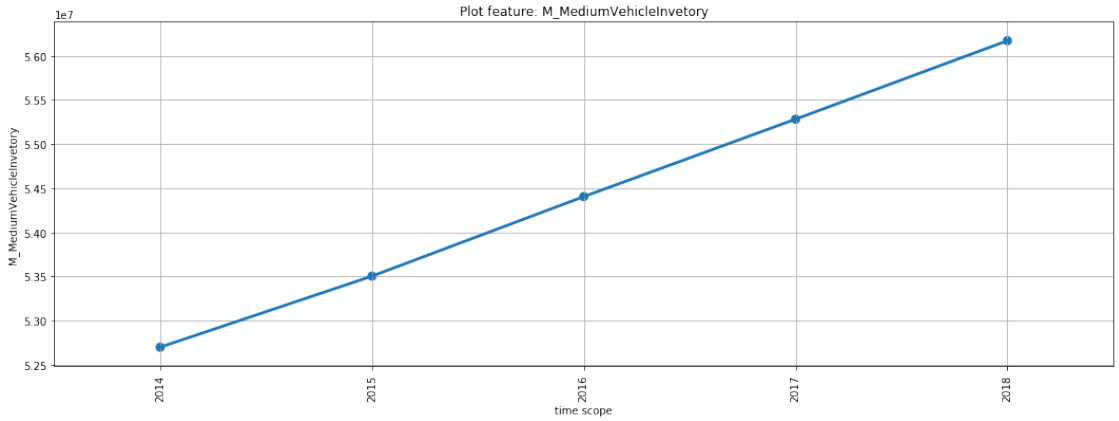
Limitations:

The data is only given for the timespan 2014 until 2018 in yearly values.

```
In [7]: # Load your data (specify file path - upload your file first)
        df = pd.read_csv('../data/mobility/MileageInKM_yearly.csv')
        # Add to database
        columns = list(df)
        columns.pop(0)
        # The for loop is only necessary if you have multiple features in the same CSV
        for i in columns:
                database[i] = {}
                database[i]['sector'] = 'mobility'
                database[i]['category'] = 'traffic'
                database[i]['yearly_data'] = True

                # Create Pandas DataFrame for single feature
                timeseries=df['date'].to_frame().join(df[i])
                timeseries = timeseries.set_index('date')
                # Convert dataframe to JSON format
                database[i]['data'] = timeseries.to_json()

                plot_data(timeseries, i, ticks_spacing = 1)
```







2.1.5 Mobility Reports

Several mobility reports are available that show the different indicators during the Corona lockdown. All these reports relate to a different time span. The related value is not given, but merging the reports with the above traffic information of BAST and BAYSIS extends these datasets up to the most recent month.

BAST Mobility Report Overview of the data:
Timespan: March 2020 until June 2020
Number of samples: 4
Features: 1

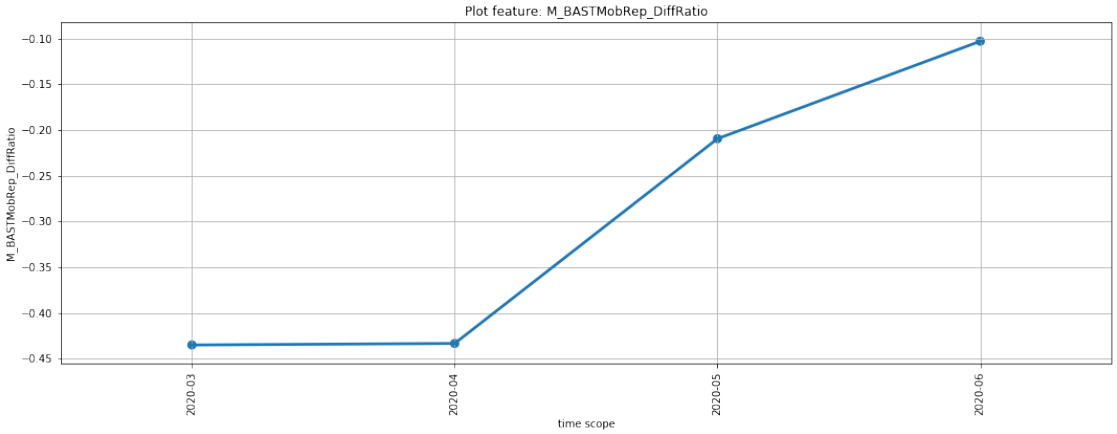
Why did we choose the data source and how it might help us:
Traffic count stations are the main feature for modeling the traffic utilization in Germany. The mobility report of BAST shows the decrease of traffic during the Corona Pandemic and therefore gives most recent information and can extend the BAST timeseries if the reference value is

given/calculated. The mobility report value of BAST is a percentage value that shows the difference in traffic utilization in Germany in relation to the timespan 2nd of February 2020 until 7th of March 2020. It will help to model the traffic during the Corona pandemic.

Dataprocessing notebook: M_ProcessMR_Apple_Google_BAST.ipynb
The weekly data is mapped to the individual days of these week and then the monthly mean is taken.

Limitations:
There is no traffic count data from BAST for the timespan 2. of February to 7th of March, which this data relates to. But there is BAYSIS traffic count data available for that timespan and with the above approach of relating bavarian and german traffic it can be modeled.

```
In [8]: # Load your data (specify file path - upload your file first)
        df = pd.read_csv('../data/mobility/BASTMobilityReport_monthly.csv')
        # Add to database
        columns = list(df)
        columns.pop(0)
        # The for loop is only necessary if you have multiple features in the same CSV
        for i in columns:
                database[i] = {}
                database[i]['sector'] = 'mobility'
                database[i]['category'] = 'traffic'
                database[i]['yearly_data'] = False

                # Create Pandas DataFrame for single feature
                timeseries=df['date'].to_frame().join(df[i])
                timeseries = timeseries.set_index('date')
                # Convert dataframe to JSON format
                database[i]['data'] = timeseries.to_json()

                plot_data(timeseries, i, ticks_spacing = 1)
```



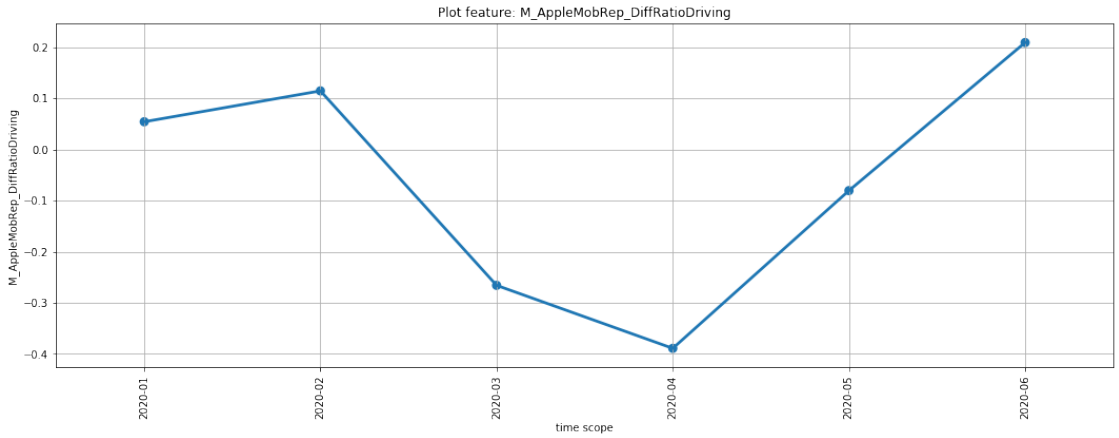
Apple Mobility Report Overview of the data:
Timespan: January 2020 until June 2020
Number of samples: 6
Features: 1

Why did we choose the data source and how it might help us:
The Apple Mobility Report data covers the areas walking, driving and public transportation. All daily values relate to the day 13th of January 2020. The data describes a relative request volume of directions via Apple Maps for countries, regions, sub regions and cities. The time relates to Pacific Standard Time. Even though the value this data relates to is not given the dataset can be usefull to compare the traffic development of sub regions.

Dataprocessing notebook: M_ProcessMR_Apple_Google_BAST.ipynb
The downloaded mobility report is processed to monthly means. The feature contains the monthly means of the relative request volume for driving directions for Germany.

Limitations:
The data relates to one day of the year (13th of January 2020). Other datasets (e.g. BAYSIS) have a monthly frequency and therefor it is difficult to bring these datasets in relation to each other.

```
In [9]: # Load your data (specify file path - upload your file first)
        df = pd.read_csv('../data/mobility/AppleMobilityReport_monthly.csv')
        # Add to database
        columns = list(df)
        columns.pop(0)
        # The for loop is only necessary if you have multiple features in the same CSV
        for i in columns:
                database[i] = {}
                database[i]['sector'] = 'mobility'
                database[i]['category'] = 'traffic'
                database[i]['yearly_data'] = False

                # Create Pandas DataFrame for single feature
                timeseries=df['date'].to_frame().join(df[i])
                timeseries = timeseries.set_index('date')
                # Convert dataframe to JSON format
                database[i]['data'] = timeseries.to_json()

                plot_data(timeseries, i, ticks_spacing = 1)
```



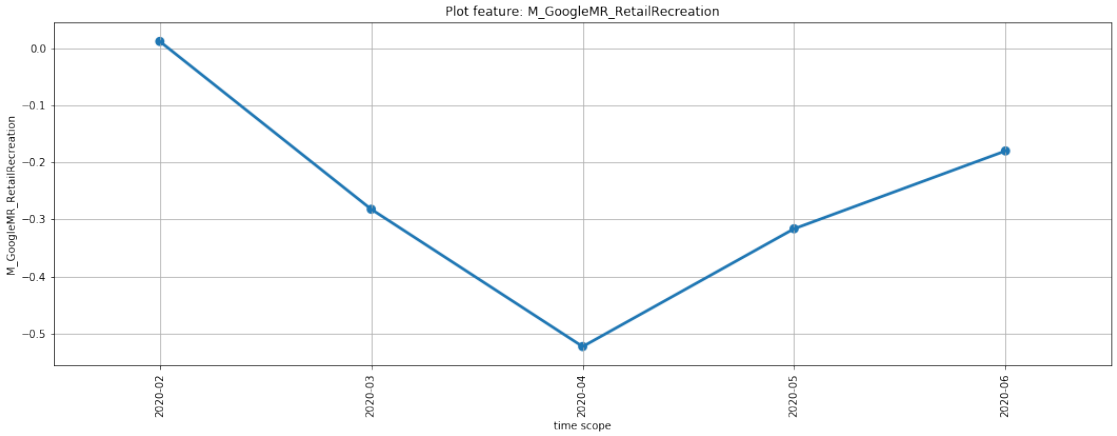
Google Mobility Report Overview of the data:
Timespan: February 2020 until June 2020
Number of samples: 5
Features: 6

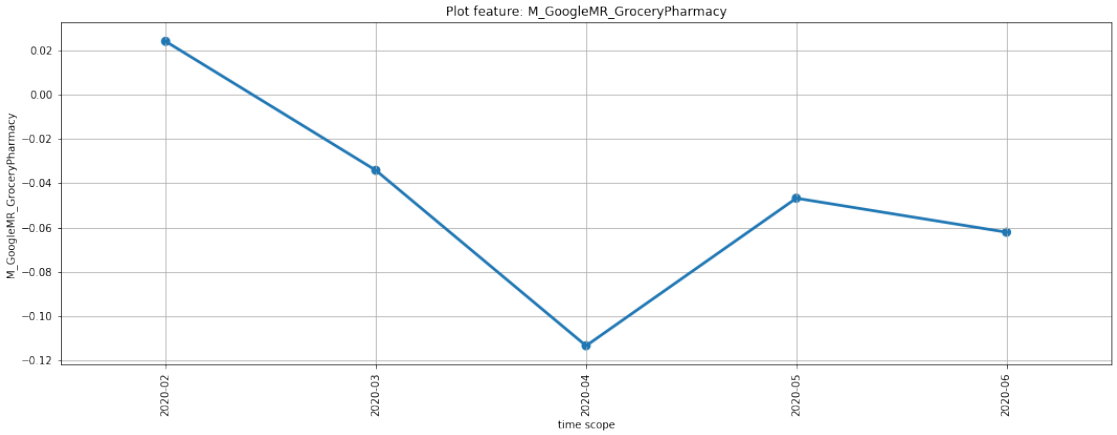
Why did we choose the data source and how it might help us:
The Google Mobility Report contains information about where people are. It covers the locations retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential. The data gives relative information to the time span 3rd of January 2020 until 6th of February 2020 and provides data on the scale of countries. The data can be used to relate the traffic information to the behavior of people like e.g. an increase in home office.
Dataprocessing notebook: M_ProcessMR_Apple_Google_BAST.ipynb
The data is downloaded and processed to monthly means for each location. The feature contains the monthly means for whole Germany.

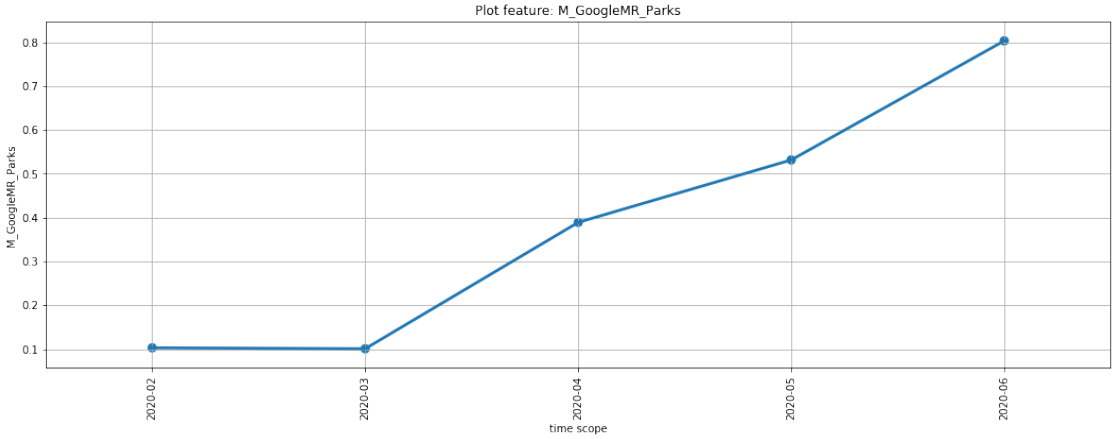
Limitations:
The data does not directly cover traffic information but rather where people are.

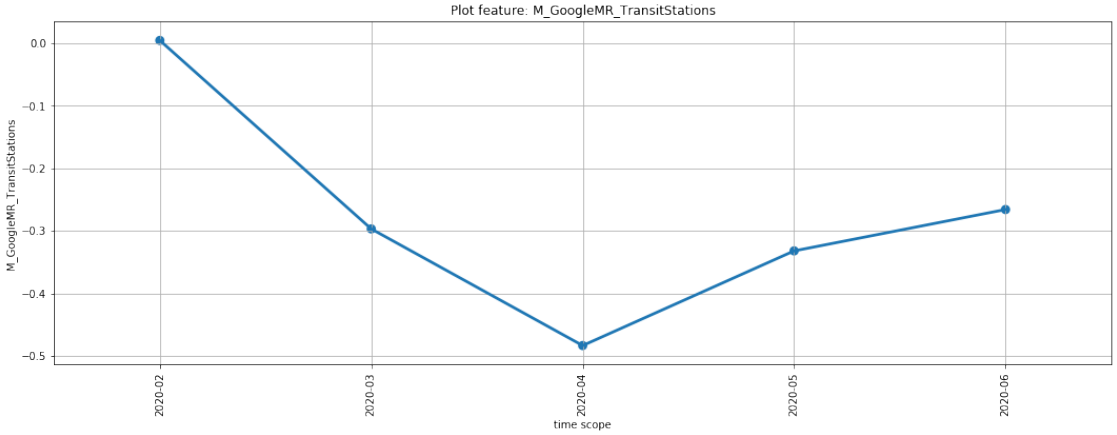
```
In [10]: # Load your data (specify file path - upload your file first)
         df = pd.read_csv('../data/mobility/GoogleMobilityReport_monthly.csv')
         # Add to database
         columns = list(df)
         columns.pop(0)
         # The for loop is only necessary if you have multiple features in the same CSV
         for i in columns:
                 database[i] = {}
                 database[i]['sector'] = 'mobility'
                 database[i]['category'] = 'traffic'
                 database[i]['yearly_data'] = False

                 # Create Pandas DataFrame for single feature
                 timeseries=df['date'].to_frame().join(df[i])
                 timeseries = timeseries.set_index('date')
                 # Convert dataframe to JSON format
```

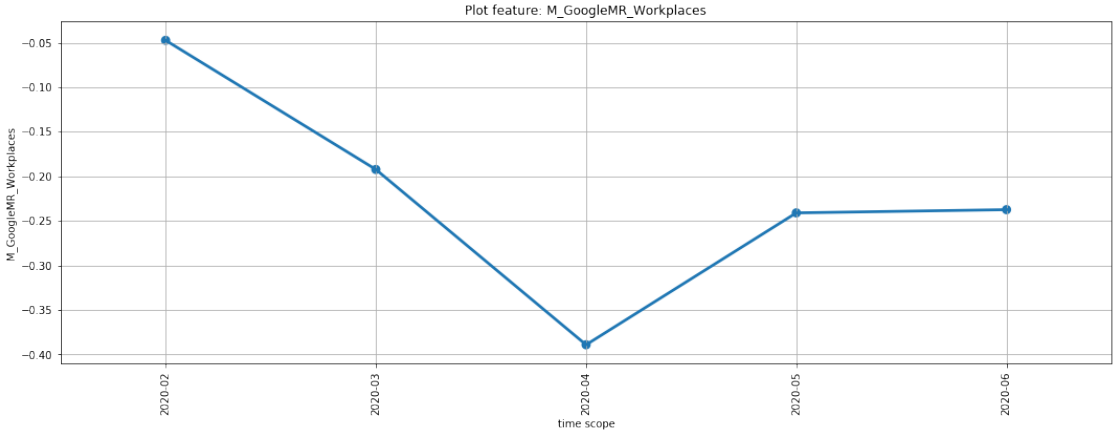
```
database[i]['data'] = timeseries.to_json()

plot_data(timeseries, i, ticks_spacing = 1)
```

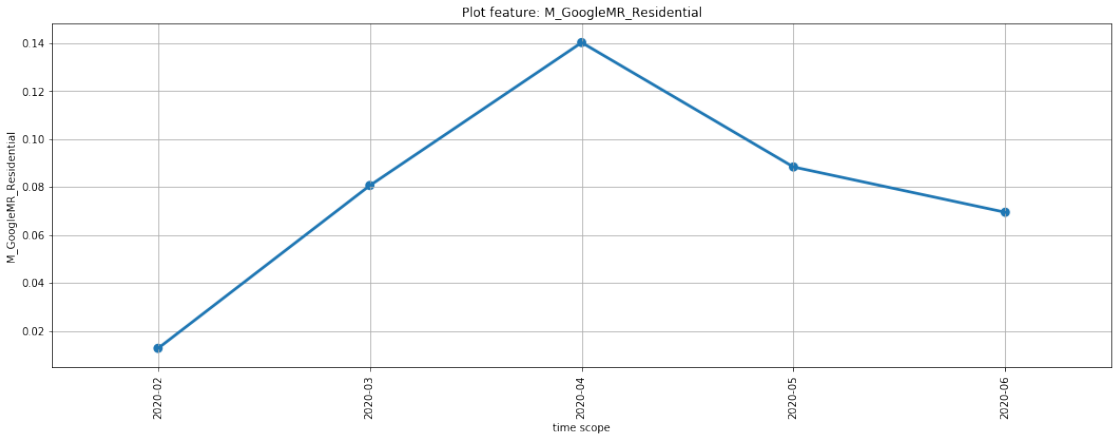







Plot feature: M_GoogleMR_TransitStations
M_GoogleMR_TransitStations
0.0
−0.1
−0.2
−0.3
−0.4
−0.5
2020-02
2020-03
2020-04
2020-05
2020-06
time scope


Plot feature: M_GoogleMR_Workplaces
M_GoogleMR_Workplaces
−0.05
−0.10
−0.15
−0.20
−0.25
−0.30
−0.35
−0.40
2020-02
2020-03
2020-04
2020-05
2020-06
time scope

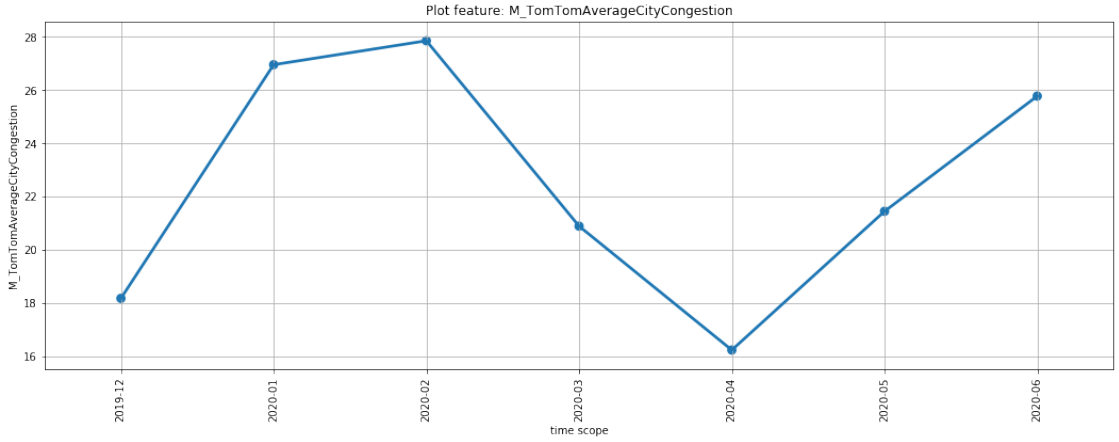

Plot feature: M_GoogleMR_Residential
M_GoogleMR_Residential
0.14
0.12
0.10
0.08
0.06
0.04
0.02
2020-02
2020-03
2020-04
2020-05
2020-06
time scope

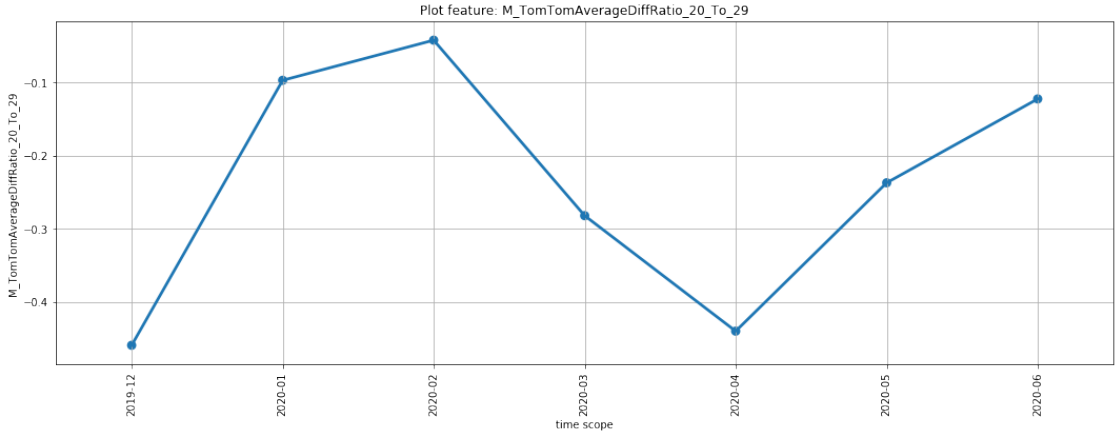
TomTom Mobility Report Overview of the data:
Timespan: January 2020 until June 2020
Number of samples: 6
Features: 2

Why did we choose the data source and how it might help us:
The TomTom dataset contains daily traffic congestion information of 416 cities in 57 countries and 6 continents. In Germany it covers 26 cities of which 25 cities contain information about the traffic congestion of 2020 in relation the correlated day in 2019. The data on the website is updated daily. It can be used to cover the traffic development of urban areas, as traffic count stations mostly cover highways and streets of type B.
Dataprocessing notebook: M_UpdateTomTom.ipynb
The daily data is automatically downloaded by a webcrawler for all of the 25 cities in Germany and processed to monthly means. Two values are processed: traffic congestion and the ratio of the traffic congestion to the correlated day in 2019 which are processed to monthly means and then averaged over the 25 cities. The feature value M_TomTomAverageCityCongestion contains the information about the mean traffic congestion in big german cities for each month and M_TomTomAverageDiffRatio_20_To_19 contains the ratio to the traffic congestion of the corresponding month in 2019.

Limitations:
The dataset only contains information about city traffic but not about highways or rural ares.

```
In [11]: # Load your data (specify file path - upload your file first)
         df = pd.read_csv('../data/mobility/AverageOfCitiesGermanyTomTom_monthly.csv')
         # Add to database
         columns = list(df)
         columns.pop(0)
         # The for loop is only necessary if you have multiple features in the same CSV
         for i in columns:
                 database[i] = {}
                 database[i]['sector'] = 'mobility'
                 database[i]['category'] = 'traffic'
                 database[i]['yearly_data'] = False

                 # Create Pandas DataFrame for single feature
                 timeseries=df['date'].to_frame().join(df[i])
                 timeseries = timeseries.set_index('date')
                 # Convert dataframe to JSON format
                 database[i]['data'] = timeseries.to_json()

                 plot_data(timeseries, i, ticks_spacing = 1)
```





2.2 Aviation

Aviation statistics for Germany Overview of the data:
Timespan: January 2011 until April 2020
Number of samples: 112 (+ 8 NAN samples)
Features: 6

Why did we choose the data source and how it might help us:
Air traffic has obviously declined sharply due to the Corona crisis. The reasons for this were travel and vacation bans. Although air traffic is only responsible for 3% of CO2 emissions in Germany, this is an important factor. Due to the high altitude where the emissions take place, the consequences are considerably worse, which is why the emissions are weighted by a factor of 3. The dataset includes 6 features which are: Number of starts, passengers per starts, freight per starts, Number of landings, passengers per landings, freight per landings. This will be used as an indicator for mapping/predicting CO2 gas emissions as well as when creating the model during the crisis for predicting future development.

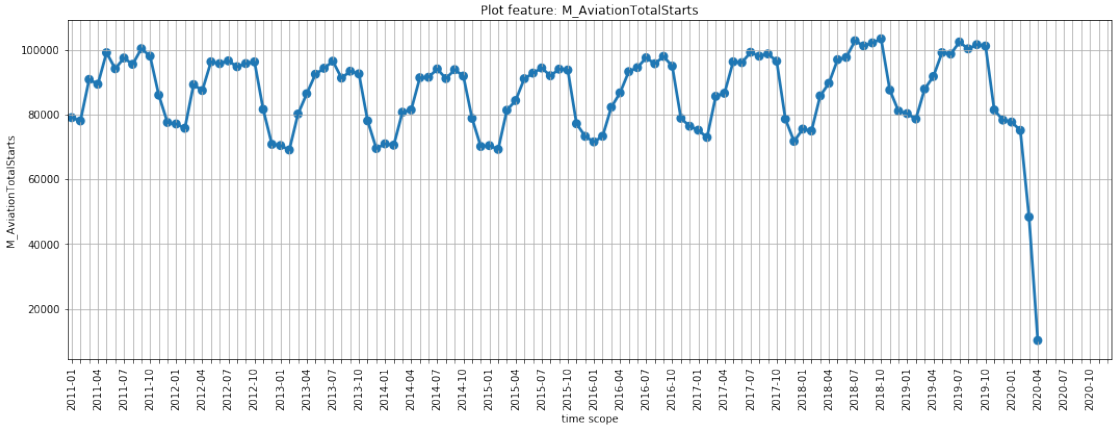
Dataprocessing Notebook: M_Process_Aviation_Dataset.ipynb

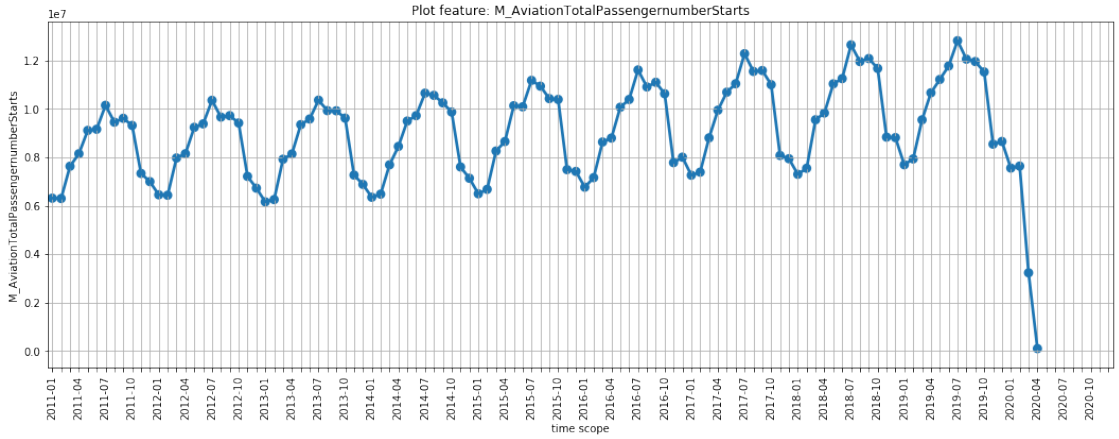
The data is manually downloaded in monthly values from GENESIS database (table nr.: 46421-0012) and later processed to fit the form of processing. Before downloading th data, Frankfurt/Main (F-FRA) is selected as the airport of interest. This limitation is not a problem, since the total values of all German airports are still included. The selection is necessary to download the data for the entire available period.

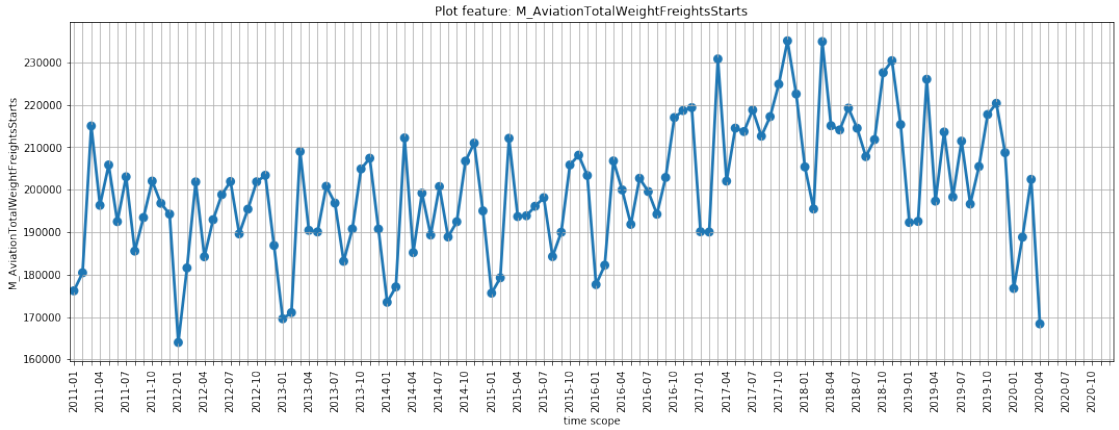
Limitations:

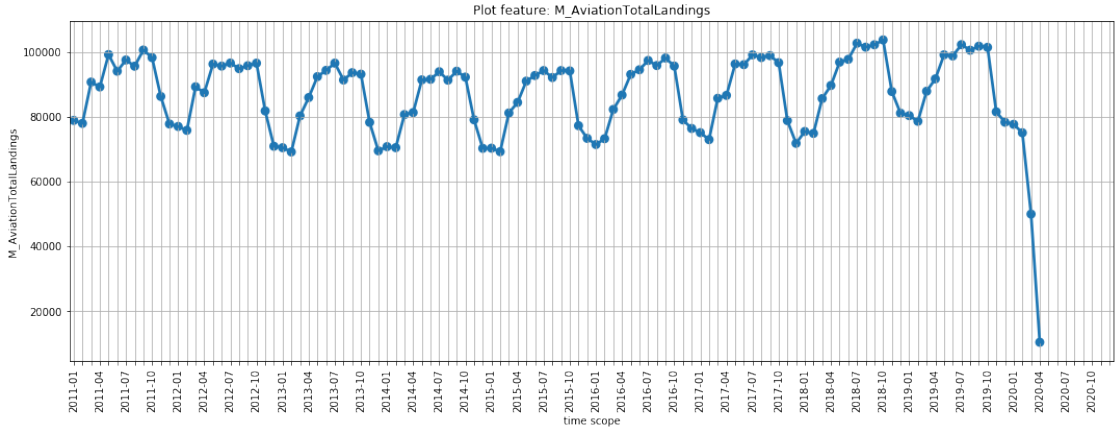
Data is only available until April and so one can only make a conclusion for the time of the lockdown. For the prediction of the future trend, current data (data after lockdown) is necessary. Need to be updated somewhen.

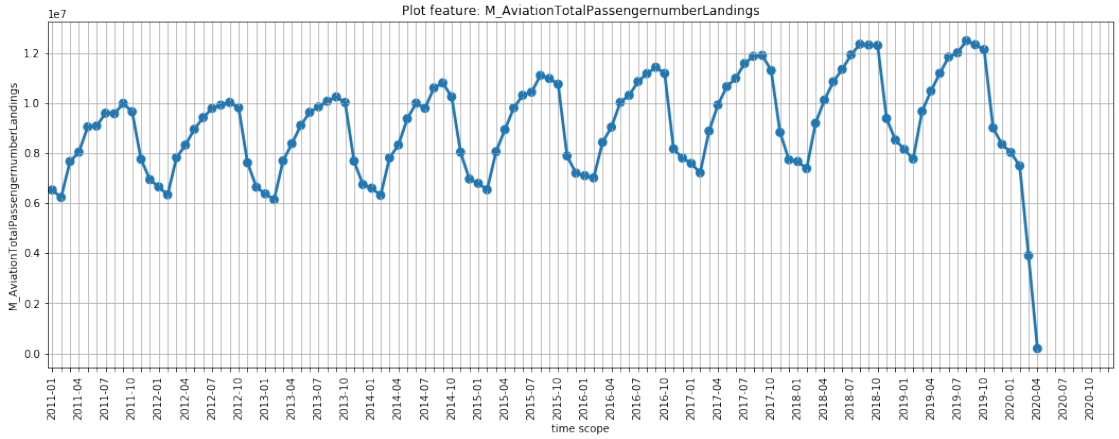
```
In [12]: # Load your data (specify file path - upload your file first)
         df = pd.read_csv('../data/mobility/Aviation_Statistics_monthly.csv')
         # Add to database
         columns = list(df)
         columns.pop(0)
         # The for loop is only necessary if you have multiple features in the same CSV
         for i in columns:
                 database[i] = {}
                 database[i]['sector'] = 'mobility'
                 database[i]['category'] = 'aviation'
                 database[i]['yearly_data'] = False

                 # Create Pandas DataFrame for single feature
                 timeseries=df['date'].to_frame().join(df[i])
                 timeseries = timeseries.set_index('date')
                 # Convert dataframe to JSON format
                 database[i]['data'] = timeseries.to_json()

                 # plot features
                 plot_data(timeseries, i)
```

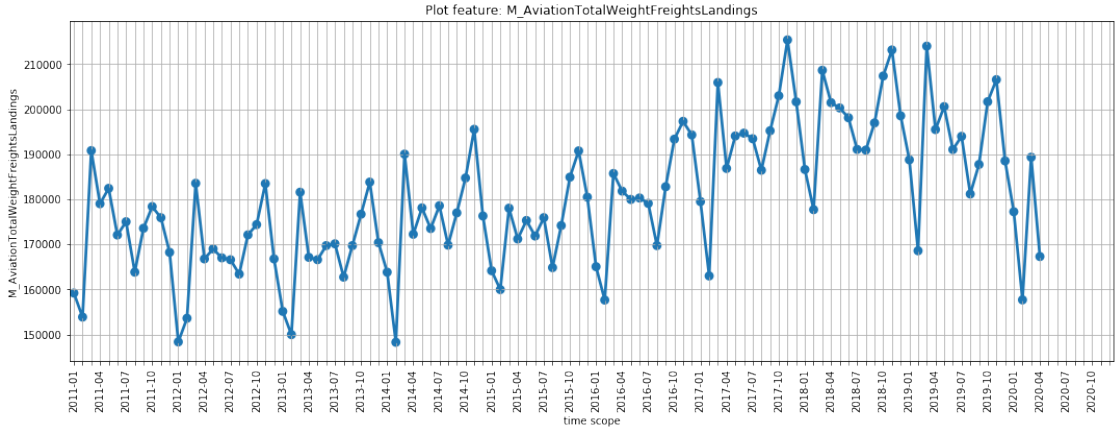



Plot feature: M_AviationTotalPassengernumberStarts
1e7
M_AviationTotalPassengernumberStarts
time scope


Plot feature: M_AviationTotalWeightFreightsStarts
M_AviationTotalWeightFreightsStarts
time scope


Plot feature: M_AviationTotalLandings
M_AviationTotalLandings
time scope





2.3 Shipping

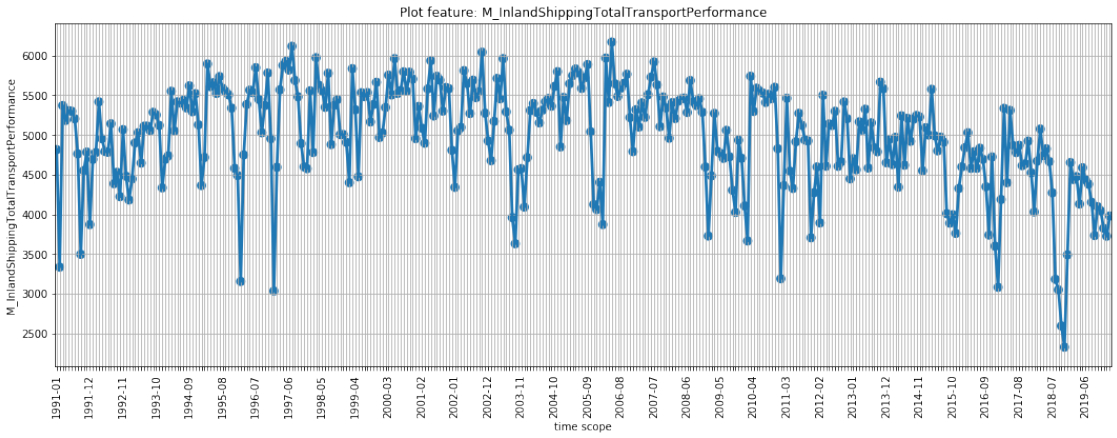
Inland freight shipping (Binnenschifffahrt) Overview of the data:
Timespan: January 1991 until February 2020
Number of samples: 350
Features: 1

Why did we choose the data source and how it might help us:
Freight traffic makes up a large proportion of daily traffic in Germany and causes significant CO2 emissions. Many goods within Germany are transported by inland waterways (Binnenschifffahrt-Güterverkehr). Since the economy is suffering from the Corona crisis, it is conceivable that freight traffic and the resulting CO2 emissions have also decreased. This will be used as an indicator for mapping/predicting CO2 gas emissions as well as when creating the model during the crisis for predicting future development.

Dataprocessing Notebook: M_Process_Inlandshipping_Dataset.ipynb
The data is manually downloaded in monthly values from GENESIS database (table nr.: 46321-0002) and later processed to fit the form of processing.

Limitations:
Data is only available until February. An impact of the Corona crisis is not apparent yet. Need to be updated somewhen and evaluated again.

```
In [13]: # Load your data (specify file path - upload your file first)
         df = pd.read_csv('../data/mobility/Shipping_InlandFreightTransport_monthly.csv')
         # Add to database
         columns = list(df)
         columns.pop(0)
         # The for loop is only necessary if you have multiple features in the same CSV
         for i in columns:
                 database[i] = {}
                 database[i]['sector'] = 'mobility'
                 database[i]['category'] = 'shipping'
                 database[i]['yearly_data'] = False

                 # Create Pandas DataFrame for single feature
                 timeseries=df['date'].to_frame().join(df[i])
                 timeseries = timeseries.set_index('date')
                 # Convert dataframe to JSON format
                 database[i]['data'] = timeseries.to_json()

                 # plot feature
                 plot_data(timeseries, i)
```



Seafaring Overview of the data:
Timespan: January 2011 until February 2020
Number of samples: 110
Features: 2

Why did we choose the data source and how it might help us:
Freight traffic makes up a large proportion of daily traffic in Germany and causes significant CO2

emissions. Germany is an exporting country and ships many goods all over the world. In addition, a lot of goods are imported from countries like China. Since the economy is suffering from the Corona crisis, it is conceivable that freight traffic and the resulting CO2 emissions have also decreased. This will be used as an indicator for mapping/predicting CO2 gas emissions as well as when creating the model during the crisis for predicting future development.

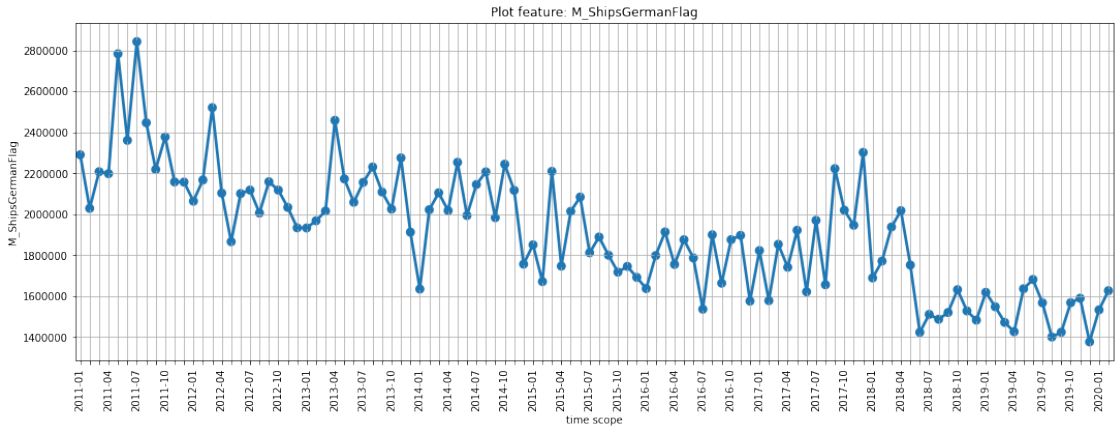
Dataprocessing Notebook: M_Process_Seafaring_Dataset.ipynb

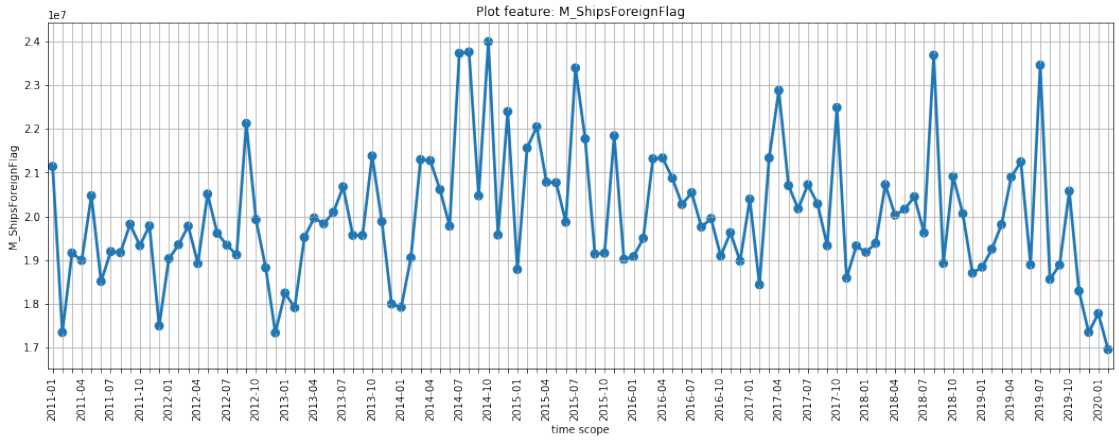
The data is manually downloaded in monthly values from GENESIS database (table nr.: 46331-0004) and later processed to fit the form of processing. Some samples had to be deleted due to incomplete data. Since a distinction was made between the groups of goods, a total sum was calculated that indicates the amount of goods transported in tons.

Limitations:

Data is only available until February. An impact of the Corona crisis is not apparent yet. Need to be updated somewhen and evaluated again.

```
In [14]: # Load your data (specify file path - upload your file first)
         df = pd.read_csv('../data/mobility/Seafaring_Statistics_monthly.csv')
         # Add to database
         columns = list(df)
         columns.pop(0)
         # The for loop is only necessary if you have multiple features in the same CSV
         for i in columns:
                 database[i] = {}
                 database[i]['sector'] = 'mobility'
                 database[i]['category'] = 'shipping'
                 database[i]['yearly_data'] = False

                 # Create Pandas DataFrame for single feature
                 timeseries=df['date'].to_frame().join(df[i])
                 timeseries = timeseries.set_index('date')
                 # Convert dataframe to JSON format
                 database[i]['data'] = timeseries.to_json()

                 # plot feature
                 plot_data(timeseries, i)
```





2.4 Railway

Railway freight transport Overview of the data:
Timespan: January 2005 until February 2020
Number of samples: 182
Features: 1

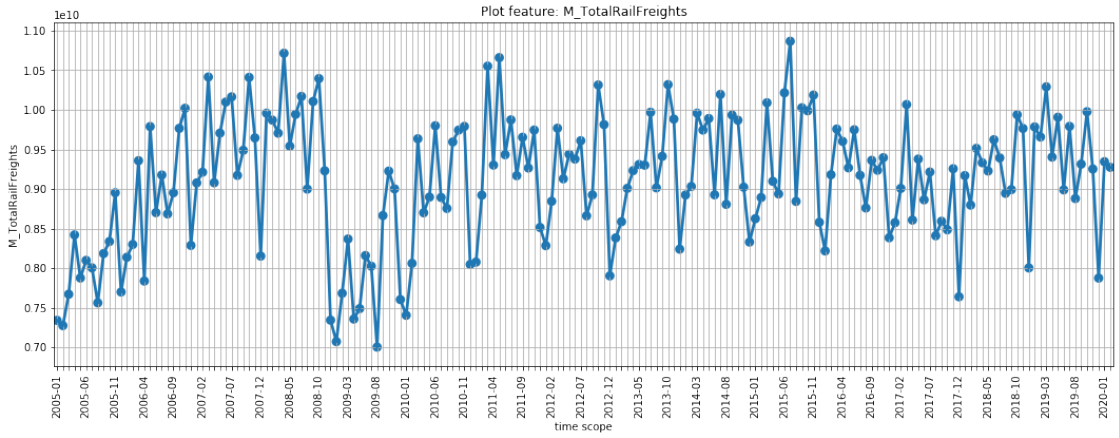
Why did we choose the data source and how it might help us:
Freight traffic makes up a large proportion of daily traffic in Germany and causes significant CO2 emissions. Many goods within Germany are transported by trains. Since the economy is suffering from the Corona crisis, it is conceivable that freight traffic and the resulting CO2 emissions have also decreased. This will be used as an indicator for mapping/predicting CO2 gas emissions as well as when creating the model during the crisis for predicting future development.

Dataprocessing Notebook: M_Process_RailwayFreight_Dataset.ipynb
The data is manually downloaded in monthly values from GENESIS database (table nr.: 46131-0004) and later processed to fit the form of processing.

Limitations:
Data is only available until February. An impact of the Corona crisis is not apparent yet. Need to be updated somewhen and evaluated again.

```
In [15]: # Load your data (specify file path - upload your file first)
         df = pd.read_csv('../data/mobility/Railway_FreightTransport_monthly.csv')
         # Add to database
         columns = list(df)
         columns.pop(0)
         # The for loop is only necessary if you have multiple features in the same CSV
         for i in columns:
                 database[i] = {}
                 database[i]['sector'] = 'mobility'
                 database[i]['category'] = 'railway'
```

```
database[i]['yearly_data'] = False

# Create Pandas DataFrame for single feature
timeseries=df['date'].to_frame().join(df[i])
timeseries = timeseries.set_index('date')
# Convert dataframe to JSON format
database[i]['data'] = timeseries.to_json()

# plot feature
plot_data(timeseries, i)
```



3 Economy

3.1 Economic Indicators

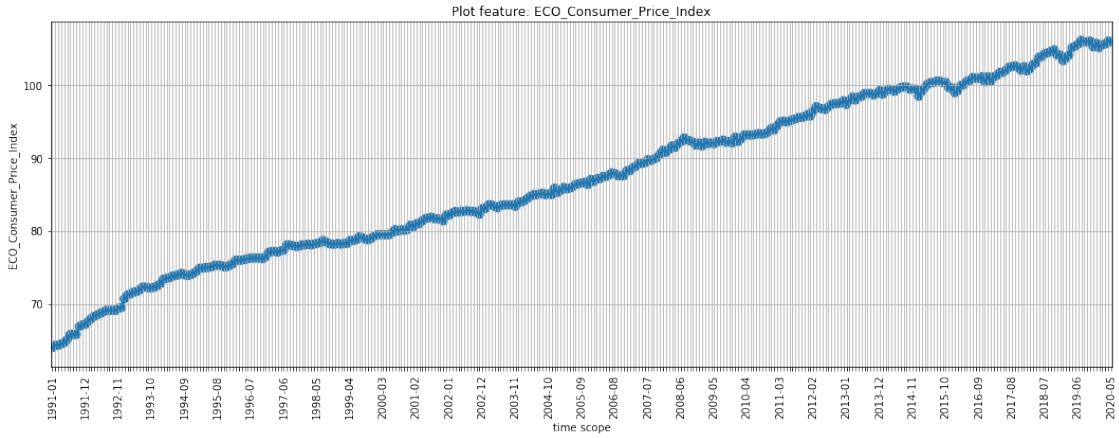
3.1.1 Consumer Price Index

Overview of the data:
Timespan DAX: 01/1991 until 05/2020
Frequency: montly
Number of samples: 354
Features: 1
Why did we choose the data source and how it might help us:
The economy is closely correlated to the producing industry which is one of the biggest sources of greenhouse gas emmissions in germany. The consumer price index gives a relative value about the change of the prices for general goods in the last years. It is closely related to the inflation rate and should also correlate with supply and demand.

Dataprocessing Notebook: ECO_Process_Consumer_Price_Index.ipynb
The data is manually downloaded in monthly values from GENESIS database (table nr.: 61111-0002) and later processed to fit the form of processing.

```
In [16]: df = pd.read_csv('../data/economy/ECO_Consumer_Price_Index.csv')
```

```
# Add to database
columns = list(df)
columns.pop(0)
# The for loop is only necessary if you have multiple features in the same CSV
for i in columns:
        database[i] = {}
        database[i]['sector'] = 'economy'
        database[i]['category'] = 'economic_indicator'
        database[i]['yearly_data'] = False

        # Create Pandas DataFrame for single feature
        timeseries=df['date'].to_frame().join(df[i])
        timeseries = timeseries.set_index('date')

        # Convert dataframe to JSON format
        database[i]['data'] = timeseries.to_json()
        plot_data(timeseries, i)
```



3.1.2 Number of Unemployment

Overview of the data:
Timespan DAX: 01/2005 until 05/2020
Frequency: montly
Number of samples: 185
Features: 1
Why did we choose the data source and how it might help us:
The economy is closely correlated to the producing industry which is one of the biggest sources of greenhouse gas emmissions in germany. The number of unemployed people in a country should be one of the most important indicators about the economic situation. During a crisis, the loss of jobs is a definite effect, even though there are programs by the state to reduce this number.

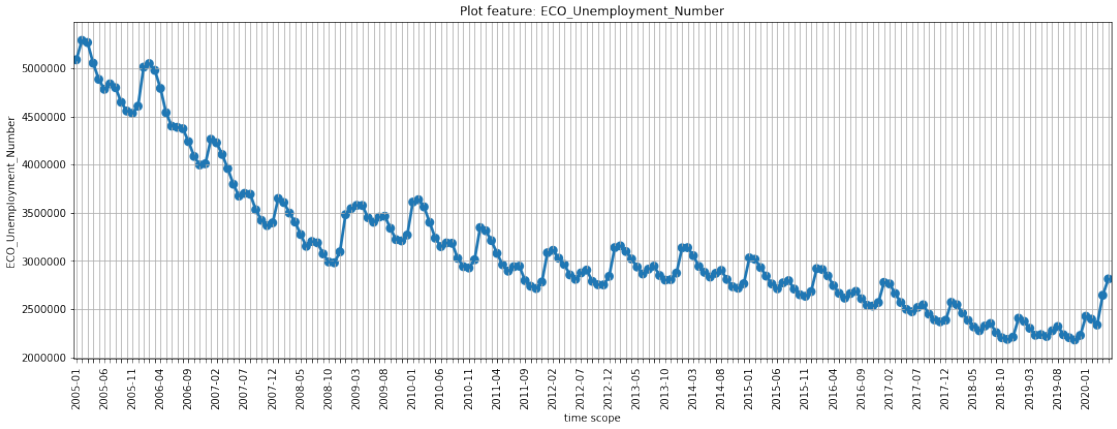
Dataprocessing Notebook: ECO_Process_Unemployment.ipynb

The data is manually downloaded in monthly values from GENESIS database (table nr.: 13211-0002) and later processed to fit the form of processing.

Limitations:

Data is only available from January 2005. So this indicator can not be used to fit/model older data.

```
In [17]: df = pd.read_csv('../data/economy/ECO_Number_Unemployment.csv')

         # Add to database
         columns = list(df)
         columns.pop(0)
         # The for loop is only necessary if you have multiple features in the same CSV
         for i in columns:
                 database[i] = {}
                 database[i]['sector'] = 'economy'
                 database[i]['category'] = 'economic_indicator'
                 database[i]['yearly_data'] = False

                 # Create Pandas DataFrame for single feature
                 timeseries=df['date'].to_frame().join(df[i])
                 timeseries = timeseries.set_index('date')

                 # Convert dataframe to JSON format
                 database[i]['data'] = timeseries.to_json()
                 plot_data(timeseries, i)
```



3.2 Stock Market

3.2.1 DAX

Overview of the data:

Timespan DAX: 1990 until today
Frequency: montly
Number of samples: 366

Features: 1

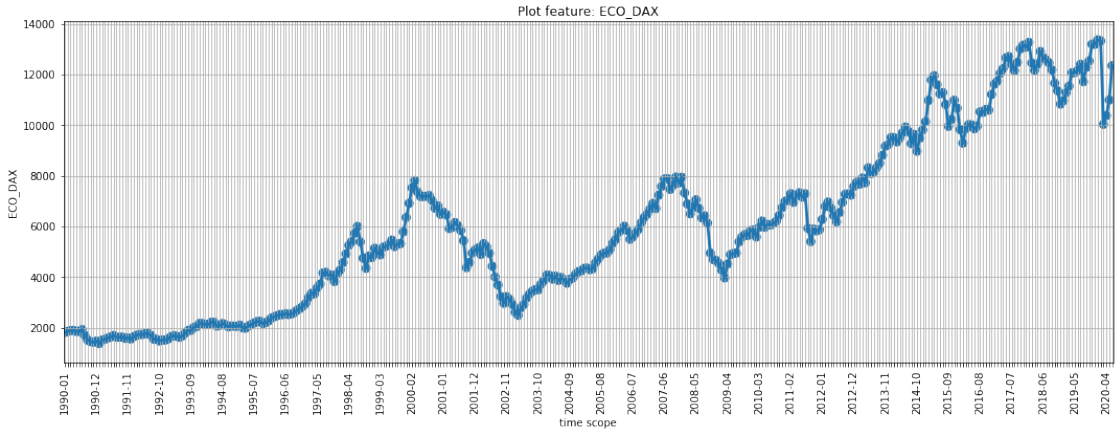
Why did we choose the data source and how it might help us:

The economy is closely correlated to the producing industry which is one of the biggest sources of greenhouse gas emmissions in germany. The DAX course is a easy to get indicator about the biggest companies of the country. The values can be read daily, giving more up-to-date information about the economy than all the other possible indicators.

Dataprocessing Notebook: ECO_Process_DAX.ipynb

The data is manually downloaded in daily values from yahoo finance and later processed to give mean values for months. In the notebook the data is also preprocessed to fit with this notebook.

```
In [18]: df = pd.read_csv('../data/economy/ECO_DAX.csv')

         # Add to database
         columns = list(df)
         columns.pop(0)
         # The for loop is only necessary if you have multiple features in the same CSV
         for i in columns:
                 database[i] = {}
                 database[i]['sector'] = 'economy'
                 database[i]['category'] = 'stock_market'
                 database[i]['yearly_data'] = False

                 # Create Pandas DataFrame for single feature
                 timeseries=df['date'].to_frame().join(df[i])
                 timeseries = timeseries.set_index('date')

                 # Convert dataframe to JSON format
                 database[i]['data'] = timeseries.to_json()
                 plot_data(timeseries, i)
```



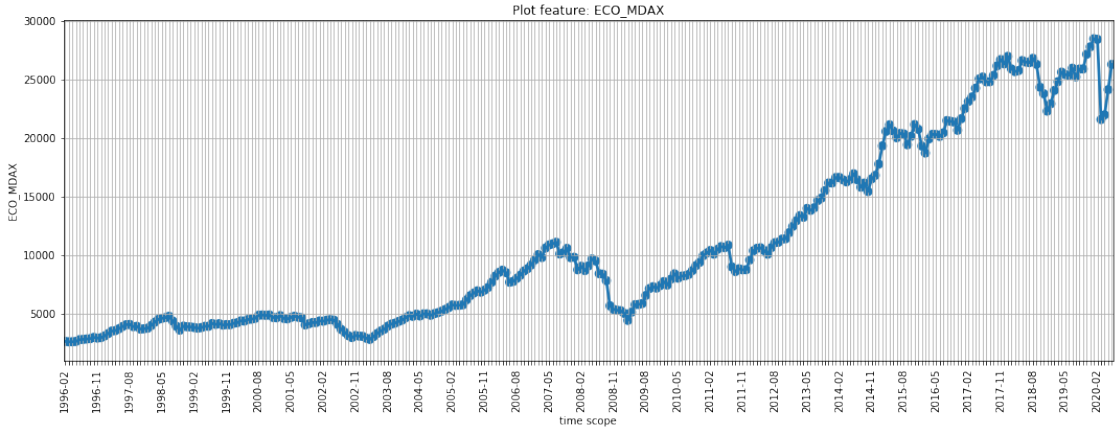
3.2.2 MDAX

Overview of the data:
Timespan DAX: 02/1996 until today
Frequency: montly
Number of samples: 293
Features: 1
Why did we choose the data source and how it might help us:
The economy is closely correlated to the producing industry which is one of the biggest sources of greenhouse gas emmissions in germany. The MDAX rate is similar to the DAX rate, but gives an overview about the medium-sized companies in the country. Like for the DAX, it is a easy to get indicator about the mid tier companies of the country. The values can be read daily, giving more up-to-date information about the economy than all the other possible indicators.

Dataprocessing Notebook: ECO_Process_MDAX.ipynb
The data is manually downloaded in daily values from yahoo finance and later processed to give mean values for months. In the notebook the data is also preprocessed to fit with this notebook.

```
In [19]: df = pd.read_csv('../data/economy/ECO_MDAX.csv')
```

```
# Add to database
columns = list(df)
columns.pop(0)
# The for loop is only necessary if you have multiple features in the same CSV
for i in columns:
        database[i] = {}
        database[i]['sector'] = 'economy'
        database[i]['category'] = 'stock_market'
        database[i]['yearly_data'] = False

        # Create Pandas DataFrame for single feature
        timeseries=df['date'].to_frame().join(df[i])
        timeseries = timeseries.set_index('date')

        # Convert dataframe to JSON format
        database[i]['data'] = timeseries.to_json()
        plot_data(timeseries, i)
```



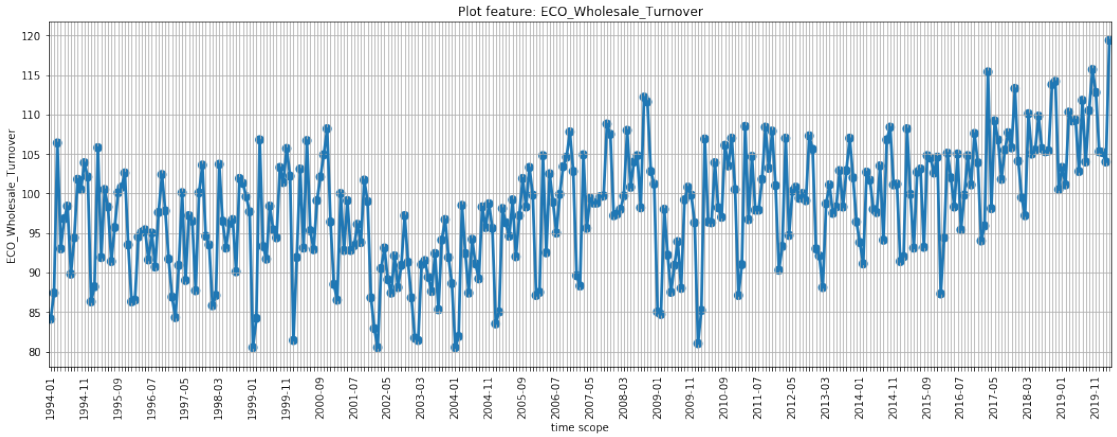
3.3 Economic Sectors

3.3.1 Turnover Wholesale

Overview of the data:
Timespan DAX: 01/1994 until 04/2020
Frequency: montly
Number of samples: 316
Features: 1
Why did we choose the data source and how it might help us:
The economy is closely correlated to the producing industry which is one of the biggest sources of greenhouse gas emmissions in germany. The turnover of wholesale stores could give insights about the willingness to take risks of small businesses.

Dataprocessing Notebook: ECO_Process_Wholesale.ipynb
The data is manually downloaded in monthly values from GENESIS database (table nr.: 45211-0005) and later processed to fit the form of processing.

```
In [20]: df = pd.read_csv('../data/economy/ECO_Wholesale_Turnover.csv')

         # Add to database
         columns = list(df)
         columns.pop(0)
         # The for loop is only necessary if you have multiple features in the same CSV
         for i in columns:
                 database[i] = {}
                 database[i]['sector'] = 'economy'
                 database[i]['category'] = 'economic_sector'
                 database[i]['yearly_data'] = False

                 # Create Pandas DataFrame for single feature
                 timeseries=df['date'].to_frame().join(df[i])
                 timeseries = timeseries.set_index('date')

                 # Convert dataframe to JSON format
                 database[i]['data'] = timeseries.to_json()
                 plot_data(timeseries, i)
```



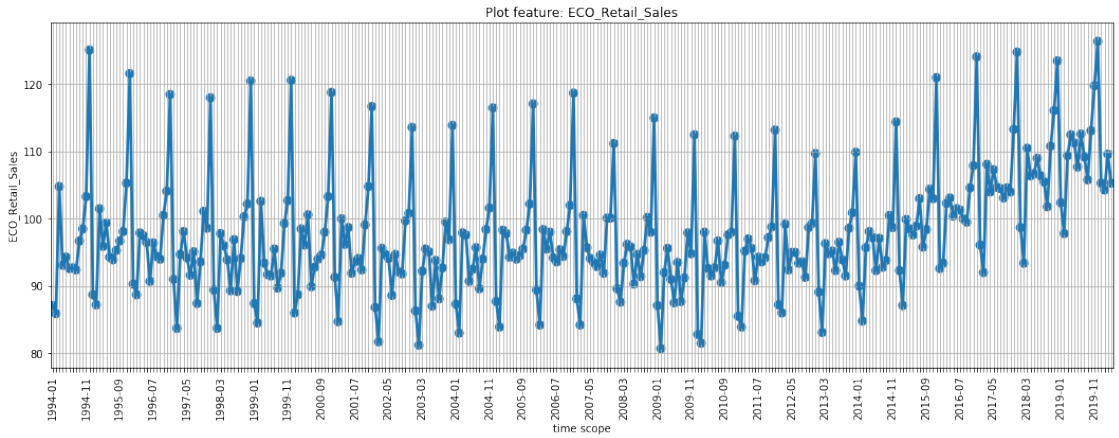
3.3.2 Turnover Retail

Overview of the data:
Timespan DAX: 01/1994 until 04/2020
Frequency: montly
Number of samples: 316
Features: 1
Why did we choose the data source and how it might help us:
The economy is closely correlated to the producing industry which is one of the biggest sources of greenhouse gas emmissions in germany. The turnover of retail stores gives good information about what is bought on a regular basis by customers. Since the purchasing power of the consumers relates to their situation, it should give some insights about the economy.

Dataprocessing Notebook: ECO_Process_Retail.ipynb
The data is manually downloaded in monthly values from GENESIS database (table nr.: 45212-0004) and later processed to fit the form of processing.

```
In [21]: df = pd.read_csv('../data/economy/ECO_Retail_Turnover.csv')

         # Add to database
         columns = list(df)
         columns.pop(0)
         # The for loop is only necessary if you have multiple features in the same CSV
         for i in columns:
                 database[i] = {}
                 database[i]['sector'] = 'economy'
                 database[i]['category'] = 'economic_sector'
                 database[i]['yearly_data'] = False

                 # Create Pandas DataFrame for single feature
                 timeseries=df['date'].to_frame().join(df[i])
                 timeseries = timeseries.set_index('date')
```

```
        # Convert dataframe to JSON format
        database[i]['data'] = timeseries.to_json()
        plot_data(timeseries, i)
```



3.4 Hospitality Industry

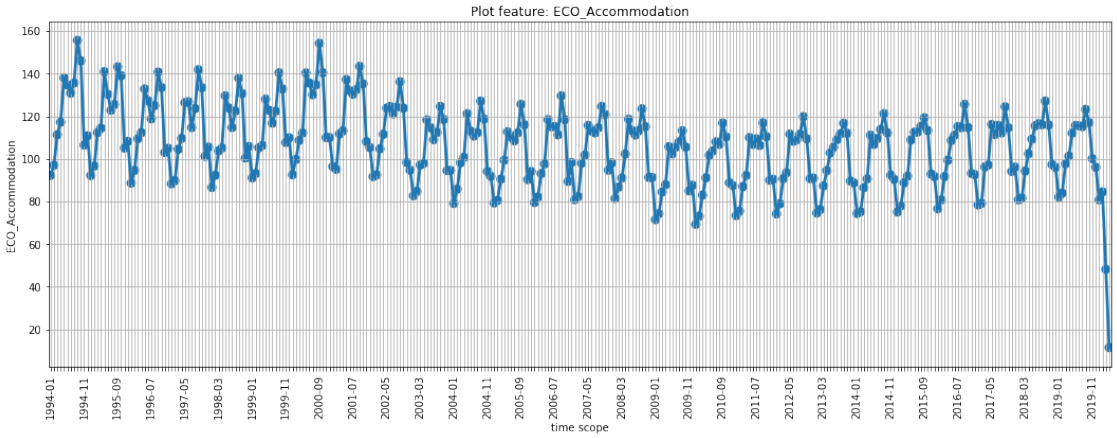
3.4.1 Turnover Accomodation

Overview of the data:
Timespan DAX: 01/1994 until 04/2020
Frequency: montly
Number of samples: 316
Features: 1
Why did we choose the data source and how it might help us:
Tourism and traveling for business purposes are normally done with a stay in another city. So the Hospitality industry could indicate the economic situation. In addition to that, there were strong impacts onto this sector by the lockdown. The turnover of accomodation represents the revenue generated by the hospitality industry. It includes all sorts of hospitality in germany.

Dataprocessing Notebook: ECO_Process_Hospitality.ipynb
The data is manually downloaded in monthly values from GENESIS database (table nr.: 45213-0005) and later processed to fit the form of processing.

```
In [22]: df = pd.read_csv('../data/economy/ECO_Accommodation.csv')

        # Add to database
        columns = list(df)
        columns.pop(0)
        # The for loop is only necessary if you have multiple features in the same CSV
        for i in columns:
                database[i] = {}
                database[i]['sector'] = 'economy'
                database[i]['category'] = 'hospitality_industry'
```

```
database[i]['yearly_data'] = False

# Create Pandas DataFrame for single feature
timeseries=df['date'].to_frame().join(df[i])
timeseries = timeseries.set_index('date')

# Convert dataframe to JSON format
database[i]['data'] = timeseries.to_json()
plot_data(timeseries, i)
```



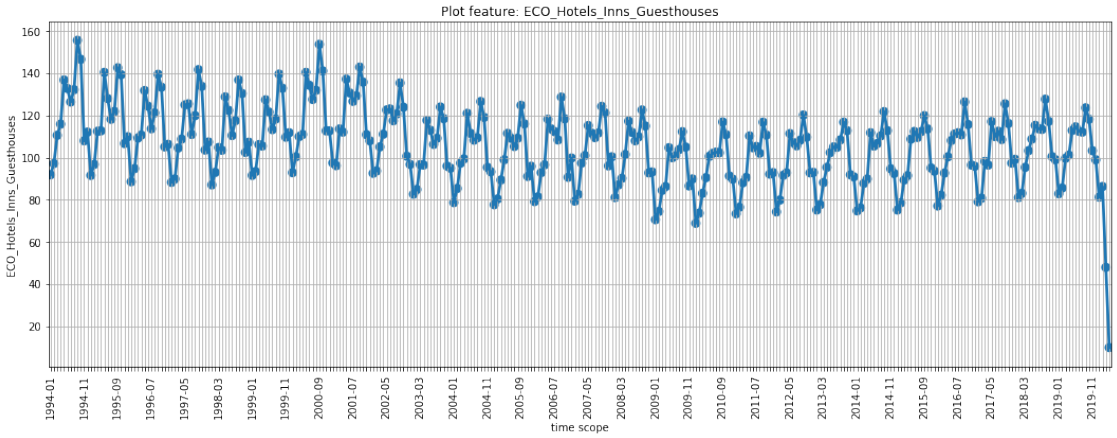
3.4.2 Turnover Hotels, Inns and Guesthouses

Overview of the data:
Timespan DAX: 01/1994 until 04/2020
Frequency: montly
Number of samples: 316
Features: 1
Why did we choose the data source and how it might help us:
Tourism and traveling for business purposes are normally done with a stay in another city. So the Hospitality industry could indicate the economic situation. In addition to that, there were strong impacts onto this sector by the lockdown. The turnover of Hotels, Inns and Guesthouses is more specific related to tourism than the gereral accommodation and could therefore indicate other trends.

Dataprocessing Notebook: ECO_Process_Hospitality.ipynb
The data is manually downloaded in monthly values from GENESIS database (table nr.: 45213-0005) and later processed to fit the form of processing.

```
In [23]: df = pd.read_csv('../data/economy/ECO_Hotels_Inns_Guesthouses.csv')

         # Add to database
         columns = list(df)
         columns.pop(0)
```

```
# The for loop is only necessary if you have multiple features in the same CSV
for i in columns:
        database[i] = {}
        database[i]['sector'] = 'economy'
        database[i]['category'] = 'hospitality_industry'
        database[i]['yearly_data'] = False

        # Create Pandas DataFrame for single feature
        timeseries=df['date'].to_frame().join(df[i])
        timeseries = timeseries.set_index('date')

        # Convert dataframe to JSON format
        database[i]['data'] = timeseries.to_json()
        plot_data(timeseries, i)
```

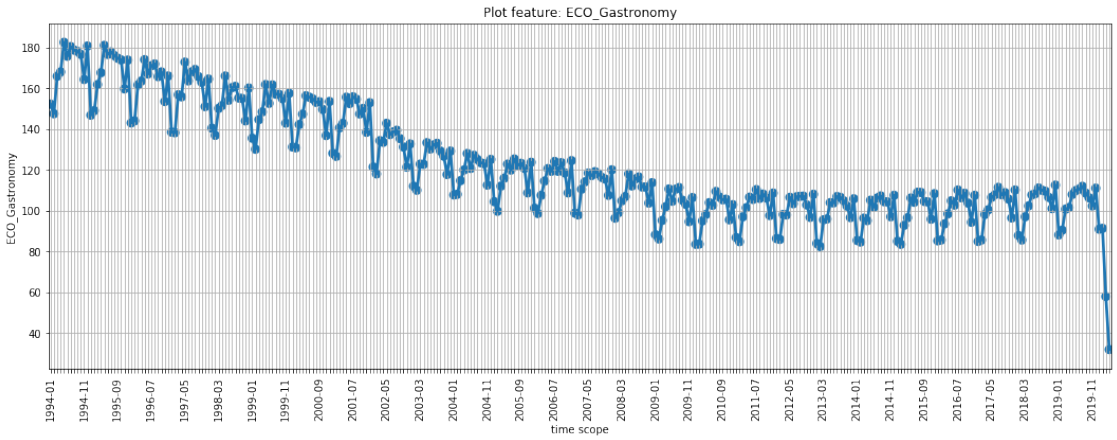


3.4.3 Turnover Gastronomy

Overview of the data:
Timespan DAX: 01/1994 until 04/2020
Frequency: montly
Number of samples: 316
Features: 1
Why did we choose the data source and how it might help us:
Tourism and traveling for business purposes are normally done with a stay in another city. So the Hospitality industry could indicate the economic situation. In addition to that, there were strong impacts onto this sector by the lockdown. Gastronomy is another important factor in this area. The turnover of gastronomy is closely related to the behavior of the people and the regulations by the government.

Dataprocessing Notebook: ECO_Process_Hospitality.ipynb
The data is manually downloaded in monthly values from GENESIS database (table nr.: 45213-0005) and later processed to fit the form of processing.

```
In [24]: df = pd.read_csv('../data/economy/ECO_Gastronomy.csv')

         # Add to database
         columns = list(df)
         columns.pop(0)
         # The for loop is only necessary if you have multiple features in the same CSV
         for i in columns:
                 database[i] = {}
                 database[i]['sector'] = 'economy'
                 database[i]['category'] = 'hospitality_industry'
                 database[i]['yearly_data'] = False

                 # Create Pandas DataFrame for single feature
                 timeseries=df['date'].to_frame().join(df[i])
                 timeseries = timeseries.set_index('date')

                 # Convert dataframe to JSON format
                 database[i]['data'] = timeseries.to_json()
                 plot_data(timeseries, i)
```



4 Energy and Household

4.0.1 Electricity generation

Electricity and Energy-related CO2 emissions in grams of different Sources
Overview of the data:
Timespan: 01/02/2002 until 01/03/2020
Number of samples: 217*7 Energy sources
Features: 7

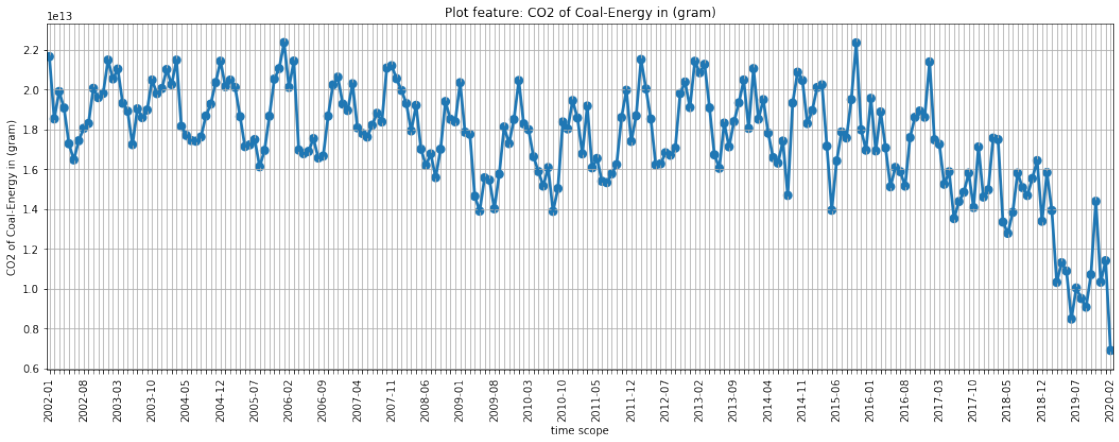
Why did we choose the data source and how it might help us:
Energy production is directly related to CO2 Emissions.The data will be used as an idicator for

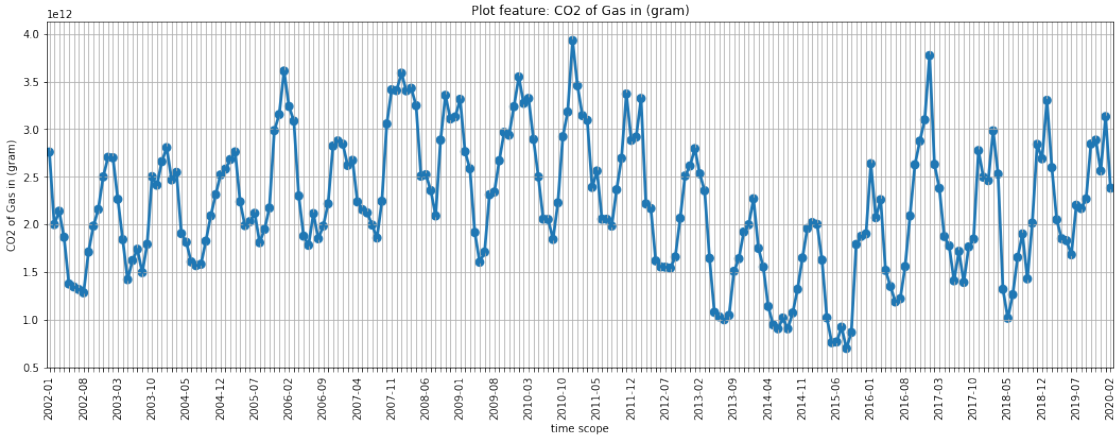
classifying greenhouse gas emissions as well as when creating the model during the crisis for predicting future development.

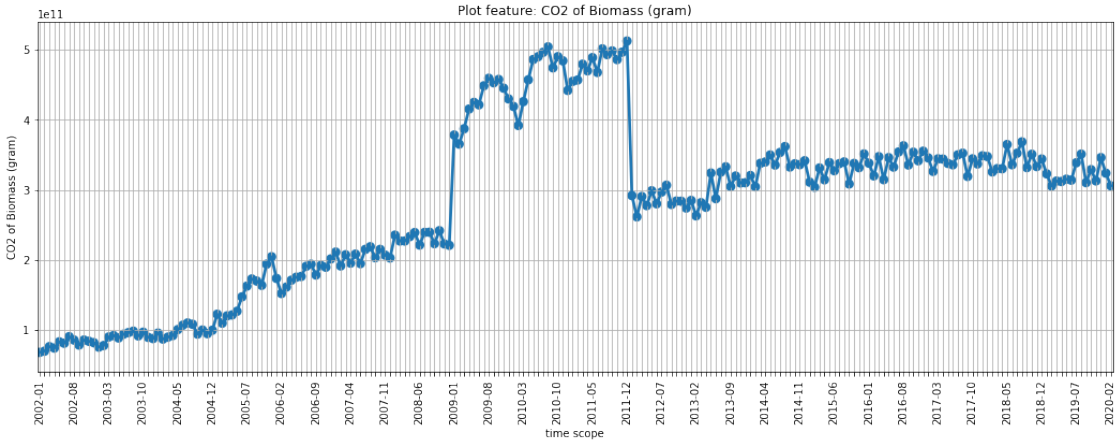
Limitations:

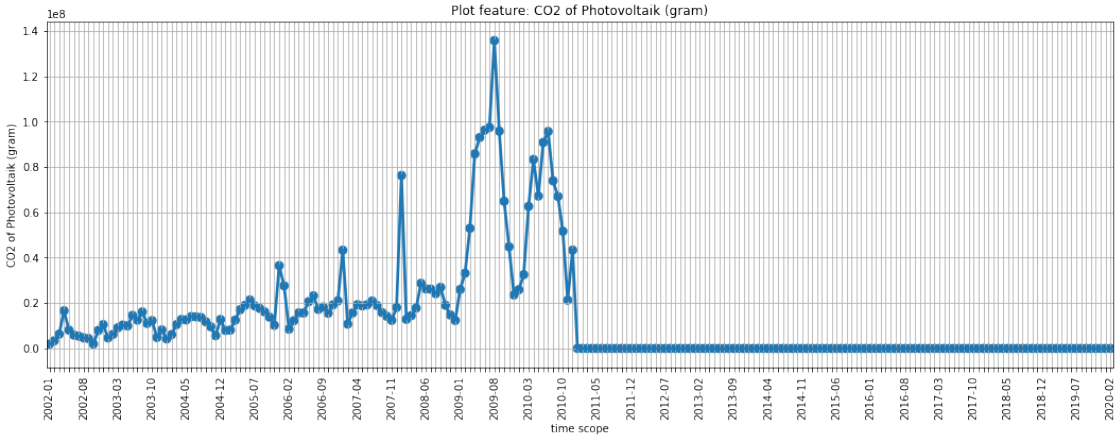
Data of Solar Energy is just available until 2011

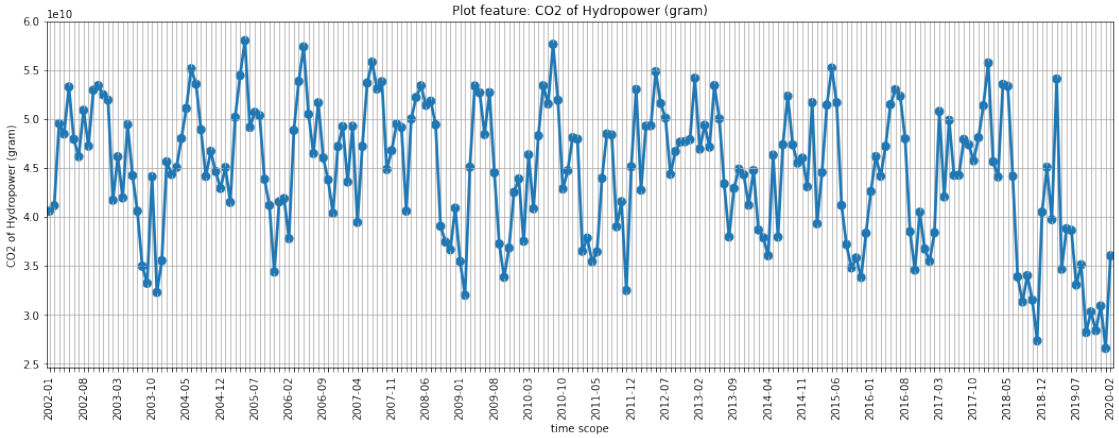
```
In [25]: df = pd.read_csv('../data/energy_households/E_ProccessEnergyCO2EMISSIONS.csv')
         # Add to database
         columns = list(df)
         columns.pop(0)

         # The for loop is only necessary if you have multiple features in the same CSV
         for i in columns:
                 database[i] = {}
                 database[i]['sector'] = 'Energy'
                 database[i]['category'] = 'Energyproduction'

                 database[i]['yearly_data'] = False

                 # Create Pandas DataFrame for single feature
                 timeseries=df['date'].to_frame().join(df[i])
                 timeseries = timeseries.set_index('date')

                 # Convert dataframe to JSON format
                 database[i]['data'] = timeseries.to_json()
                 plot_data(timeseries, i)
```

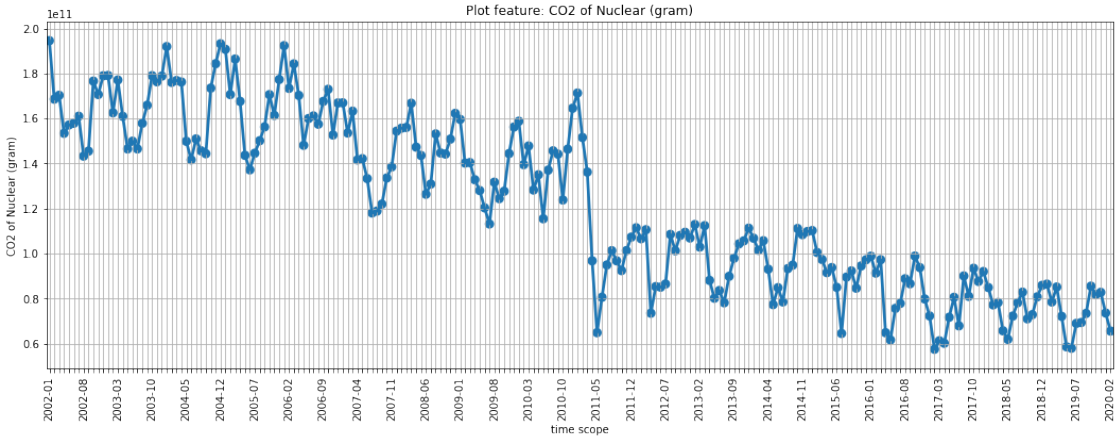


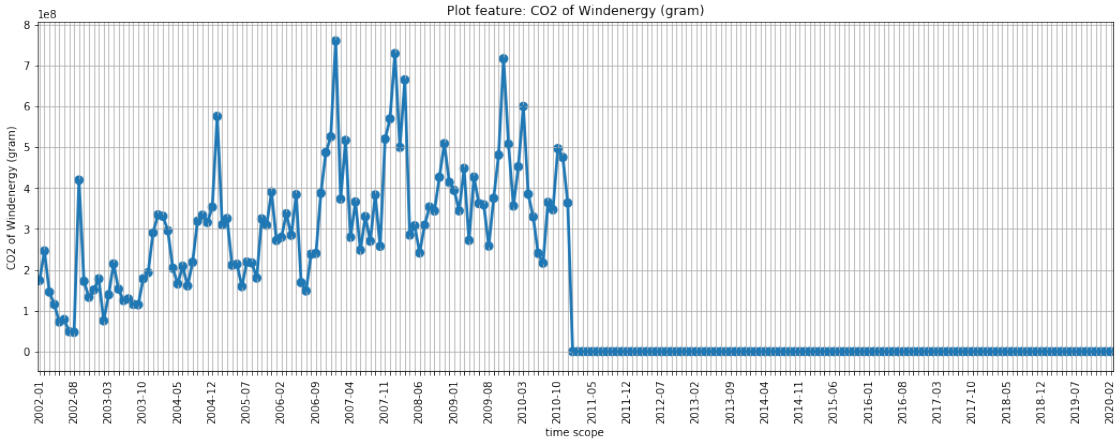

Plot feature: CO2 of Gas in (gram)
1e12
CO2 of Gas in (gram)
time scope


Plot feature: CO2 of Biomass (gram)
1e11
CO2 of Biomass (gram)
time scope


Plot feature: CO2 of Photovoltaik (gram)
1e8
CO2 of Photovoltaik (gram)
time scope


Plot feature: CO2 of Hydropower (gram)
1e10
CO2 of Hydropower (gram)
time scope


Plot feature: CO2 of Nuclear (gram)
1e11
CO2 of Nuclear (gram)
time scope


Plot feature: CO2 of Windenergy (gram)
1e8
CO2 of Windenergy (gram)
time scope

4.1 Household Data

4.1.1 Heaing oil prices

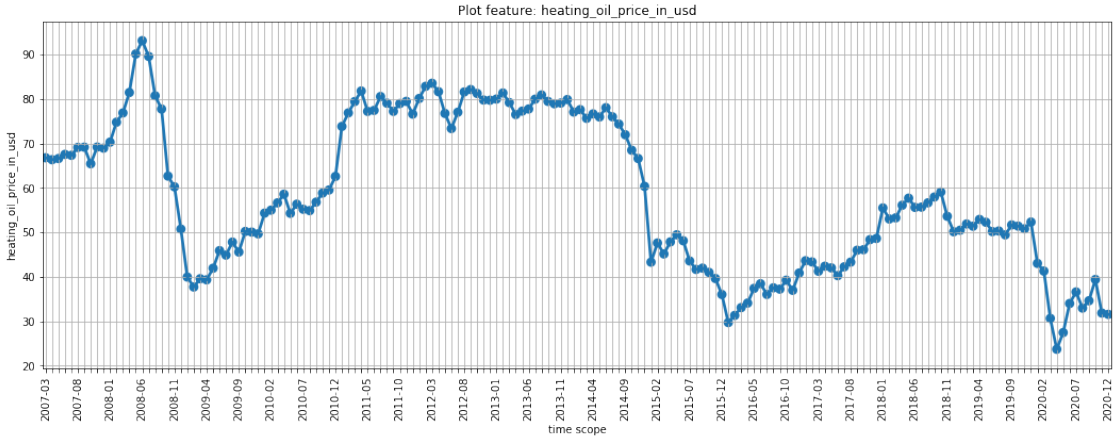
Overview of the data:
Timespan: 05/11/2007 until 19/06/2020
Number of samples: 3244
Features: 1

Why did we choose the data source and how it might help us:
Heating oil prices can be an indicator on how much heating oil is burnt for heating households. Higher demand can mean a higher price for example. One can see a downward trend during the corona crisis and the 2008 financial crisis. The data will be used as an idicator for mapping/predicting greenhouse gas emissions as well as when creating the model during the crisis for predicting future development.

Limitations:
The data is not adjusted for infaltion.

```
In [26]: df = pd.read_csv('../data/energy_households/E_HeatingOilPricesUSDmonthly.csv')
         df = df.set_index('date')
```

```
In [27]: for i in list(df):
             database[i] = {}
             database[i]['sector'] = 'energy_households'
             database[i]['category'] = 'households'
             database[i]['feature_descprition'] = i
             database[i]['yearly_data'] = False
             database[i]['data'] = df.to_json()
             plot_data(df, i)
```



4.2 Weather Data

Weather data averaged for every Bundesland and Germany.
Overview of the data:

Summary: Mean air temperature, precipitation and sunshine duration for all 16 states and Germany.
Timespan: 01/1990 until 05/2020
Number of samples: 1095
Features: 365 (for each of the 3 indicators)

Dataprocessing notebook: E_Process_Weather.ipynb

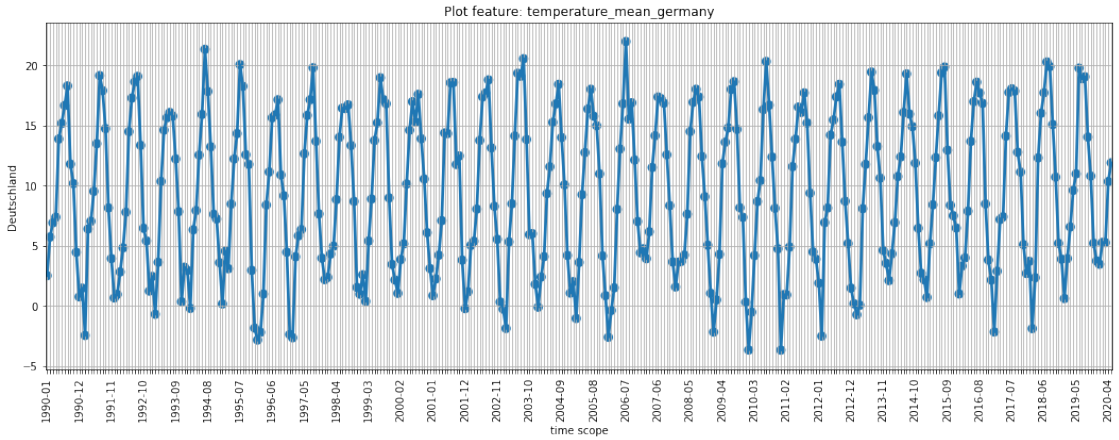
Why did we choose the data source and how it might help us:

Weather data has an indirect influence on a lot of indicators related to greenhouse gas emissions, such as energy production, usage and personal behavior. The data will be used as an idicator for classifying greenhouse gas emissions as well as when creating the model during the crisis for predicting future development.

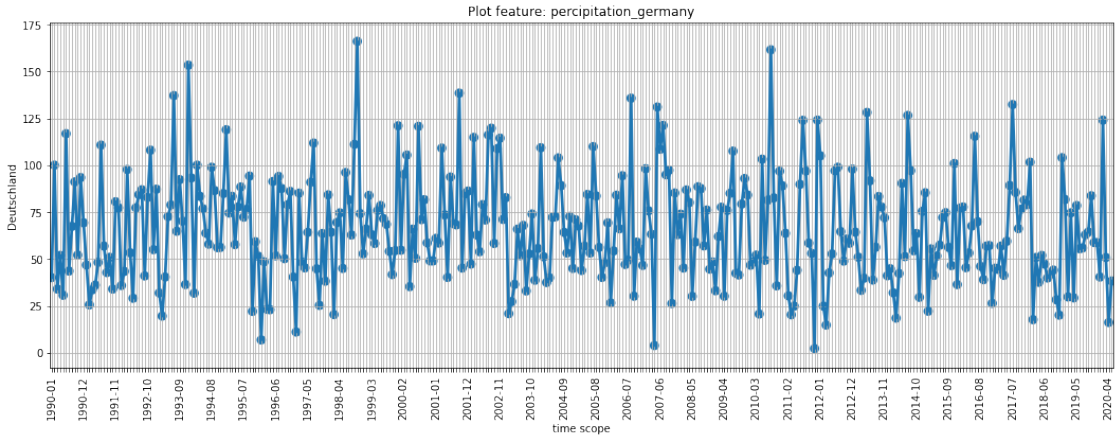
Limitations:

No obvious limitations known so far.

```
In [28]: # TEMPERATURE MEAN GERMANY
         df = pd.read_csv('../data/energy_households/E_Process_Weather_temperature_mean.csv')

         # Add to database
         feature_name = 'temperature_mean_germany'
         database[feature_name] = {}
         database[feature_name]['sector'] = 'energy_households'
         database[feature_name]['category'] = 'weather'
         database[feature_name]['yearly_data'] = False

         # Create Pandas DataFrame for single feature
         timeseries=df['date'].to_frame().join(df['Deutschland'])
         timeseries = timeseries.set_index('date')

         # Convert dataframe to JSON format
         database[feature_name]['data'] = timeseries.to_json()
         plot_data(timeseries, feature_name)
```

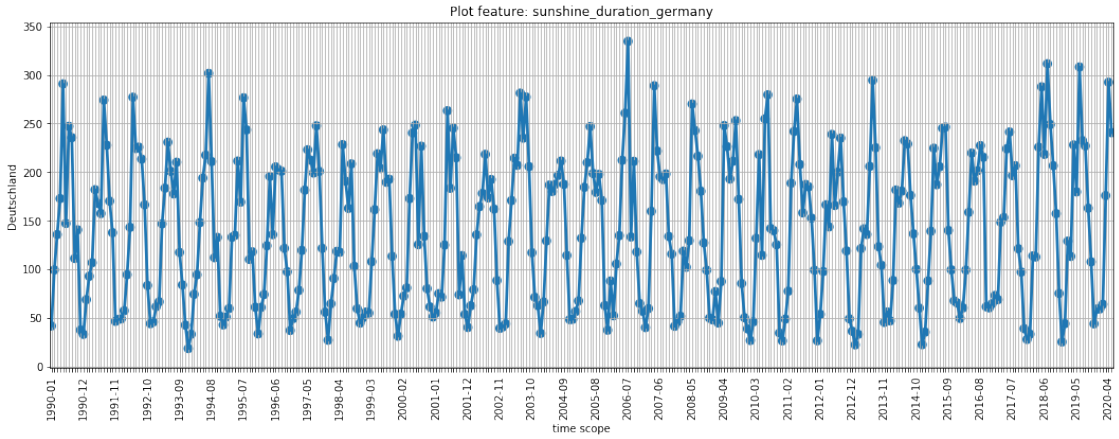


In [29]:
```
# RAIN GERMANY
df = pd.read_csv('../data/energy_households/E_Process_Weather_precipitation.csv')

# Add to database
feature_name = 'percipitation_germany'
database[feature_name] = {}
database[feature_name]['sector'] = 'energy_households'
database[feature_name]['category'] = 'weather'
database[feature_name]['yearly_data'] = False

# Create Pandas DataFrame for single feature
timeseries=df['date'].to_frame().join(df['Deutschland'])
timeseries = timeseries.set_index('date')

# Convert dataframe to JSON format
database[feature_name]['data'] = timeseries.to_json()
plot_data(timeseries, feature_name)
```



In [30]:
```
# SUNSHINE GERMANY
df = pd.read_csv('../data/energy_households/E_Process_Weather_sunshine_duration.csv')

# Add to database
feature_name = 'sunshine_duration_germany'
database[feature_name] = {}
database[feature_name]['sector'] = 'energy_households'
database[feature_name]['category'] = 'weather'
database[feature_name]['yearly_data'] = False

# Create Pandas DataFrame for single feature
timeseries=df['date'].to_frame().join(df['Deutschland'])
timeseries = timeseries.set_index('date')
```

```
# Convert dataframe to JSON format
database[feature_name]['data'] = timeseries.to_json()
plot_data(timeseries, feature_name)
```



5 Greenhouse gas emissions (CO2)

5.0.1 Target Data

CO2 emissions in million tonnes.

Overview of the data:

Timespan: 1990 until 2020 * 1990 - 2017: actually published data of "Umweltbundesamt" * 2018 - 2020: currently estimated prognosis of "Umweltbundesamt"

Number of samples: 31

Features: 1

Why did we choose the data source and how it might help us:

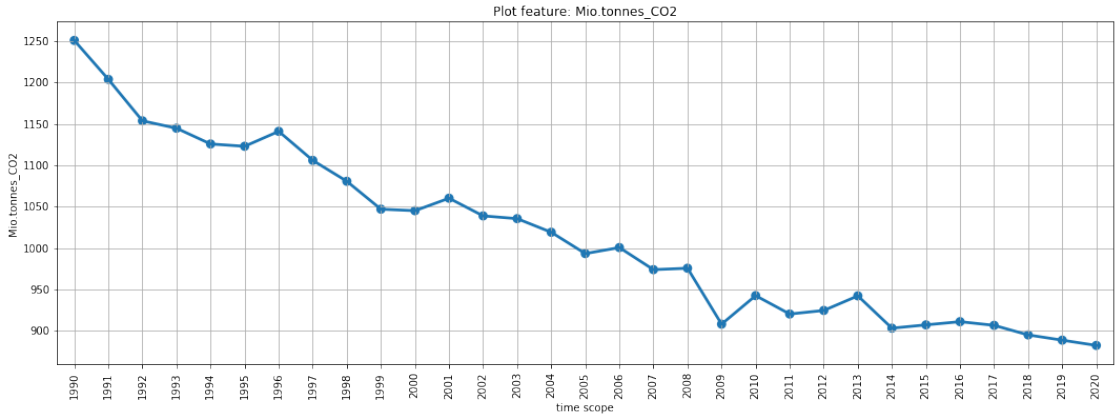
Any supervised learning task depends on labled data. This data represents our labels which we try to predict for the future and therefore map the input features to this target values.

Limitations:

None so far, since we will try to predict the yearly data emissions for the future years after year 2020. (2021, 2022, ..., 2030)

```
In [31]: df = pd.read_csv('../data/greenhouse_emissions/oeko-Institut Sektorale_Abgrenzung_Tre

         columns = list(df)
         columns.pop(0)

         for i in columns:
                 database[i] = {}
                 database[i]['sector'] = 'target_values'
                 database[i]['category'] = 'target_values'
                 database[i]['yearly_data'] = True
```

```
# Create Pandas DataFrame for single feature
timeseries=df['date'].to_frame().join(df[i])
timeseries = timeseries.set_index('date')
# Convert dataframe to JSON format
database[i]['data'] = timeseries.to_json()
# Plot feature
plot_data(timeseries, i, ticks_spacing = 1)
```



6 Export Database

After having added all features to the database, export the database as JSON file with the following command:

```
In [32]: # After adding all features, save database
         with open(f'./database.json', 'w') as outfile:
             json.dump(database, outfile)
```