Prediction of CO2 emissions from country-specific data

A Machine Learning project

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Stage 2: Data exploration and visualization

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0. Introduction

Project summary

Aim of the project: Analysis of country-specific data and development of machine learning models in order to predict CO2 emissions from country parameters. The project uses the publicly available dataset Climate Change Data from the World Bank Group, which provides data on the vast majority of countries over a range of years for parameters such as:

- country: the vast majority of countries worldwide
- year: ranging from 1990 to 2011
- various emissions of greenhouse gases such as CO2, CH4, N2O, others
- population-specific parameters: population count, urban population, population growth, etc.
- country economic indicators: GDP, GNI, Foreign Direct Investment, etc.
- land-related parameters: cereal yield, agricultural land, Nationally terrestrial protected areas, etc.
- climate data: precipitations, national disasters, etc.
- energy use
- counts of certain types of medical personnel
- etc.

The project is divided into three stages:

1. Data cleaning and preparation
2. Data exploration and visualization
3. Predictive analysis with the Random Forest machine learning algorithm

Each of the stages is described in a separate Jupyter Notebook (.ipynb file) and a derived HTML file.

Notebook summary - Stage 2: Data exploration and visualization

Aim of this notebook: The subject of this particular notebook is to gain first data insights from descriptive statistics, visualize relevant dependencies and identify global trends. This is especially necessary for the proper choice of relevant/important features and of suitable machine learning algorithms for the predictive analysis.

Input: cleaned dataset from the csv data file (output of Stage 1 of the project)

Output: plots, visualizations, summaries, trends, insights, conclusions

Programming language: Python 3.7

Libraries used in this notebook: seaborn, matplotlib, pandas, numpy

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Data source

The used data comes from the Climate Change Data of the World Bank Group, which provides country-specific data on parameters such as CO2 emissions, energy use, population count, urban population, cereal yield, nationally terrestrial protected areas, GDP, GNI, etc.

The dataset is publicly available at https://datacatalog.worldbank.org/dataset/climate-change-data and licenced under the Creative Commons Attribution 4.0 International license.

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1. Notebook Setup

Libraries and dataset import:

```python
# import all needed libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns

# import the cleaned dataset from a csv file
data = pd.read_csv(r'data_cleaned.csv')
```

2. Global overview of the available data

A global overview of the imported data yields the following insights:

```python
print("Shape of the dataset:")
data.shape
```

```
Shape of the dataset:
```

```
(1700, 18)
```

```python
print("available columns and their data types:")
data.dtypes
```

```
available columns and their data types:
```

```
country                object
year                    int64
cereal_yield          float64
fdi_perc_gdp          float64
en_per_gdp            float64
en_per_cap            float64
co2_ttl               float64
co2_per_cap           float64
co2_per_gdp           float64
pop_urb_aggl_perc     float64
```

```
prot_area_perc          float64
gdp                     float64
gni_per_cap             float64
under_5_mort_rate       float64
pop_growth_perc         float64
pop                     float64
urb_pop_growth_perc     float64
urb_pop                 float64
dtype: object
```

```
print("Overview of the first 5 rows:")
data.head()
```

```
Overview of the first 5 rows:

  country  year  cereal_yield  fdi_perc_gdp  en_per_gdp    en_per_cap
\
0     AGO  1991         417.4      5.449515  179.271884    565.451027

1     ARE  1991        1594.0      0.076475  245.977706  12262.388130

2     ARG  1991        2666.1      1.285579  173.122857   1434.960601

3     AUS  1991        1603.3      1.306912  208.686644   4926.727783

4     AUT  1991        5463.0      0.209142  128.939160   3381.073790


      co2_ttl  co2_per_cap  co2_per_gdp  pop_urb_aggl_perc
prot_area_perc  \
0    4367.397     0.409949   129.971142          15.290728
12.399822
1   57010.849    29.851550   598.807980          26.377204
0.266886
2  117021.304     3.536073   426.614517          39.119646
4.772468
3  281530.258    16.288490   689.948873          60.356798
7.915273
4   65888.656     8.448456   322.186648          19.746121
20.991143

            gdp  gni_per_cap  under_5_mort_rate  pop_growth_perc
pop  \
0  1.219375e+10        820.0              239.1         3.034866
10653515.0
1  3.391964e+10      19340.0               20.5         5.442852
1909812.0
2  1.897200e+11       3960.0               25.8         1.372593
33093579.0
3  3.299655e+11      18380.0                8.6         1.274577
17284000.0
```

```
4  1.721664e+11      21200.0                8.9         1.134999
7798899.0

   urb_pop_growth_perc       urb_pop
0             6.687032  4.099473e+06
1             5.265704  1.507988e+06
2             1.762636  2.890393e+07
3             1.438378  1.478473e+07
4             1.134999  5.131676e+06
```

```python
print("Descriptive statistics:")
data.describe()
```

```
Descriptive statistics:

              year  cereal_yield  fdi_perc_gdp   en_per_gdp
en_per_cap  \
count  1700.000000   1700.000000   1700.000000  1700.000000
1700.000000
mean   1999.570588   3013.317581      2.948940   249.822736
1968.979736
std       5.143070   1796.206082      3.949722   186.195019
1959.419972
min    1991.000000    175.700000    -15.027675    66.335372
116.511476
25%    1995.000000   1683.364736      0.834105   136.320490
542.882788
50%    2000.000000   2584.800000      1.993220   197.624918
1089.225939
75%    2004.000000   3933.400000      3.702149   286.474936
2893.996077
max    2008.000000   8410.800000     51.373951  1383.380011
12607.839262

            co2_ttl  co2_per_cap  co2_per_gdp  pop_urb_aggl_perc  \
count  1.700000e+03  1700.000000  1700.000000        1700.000000
mean   9.793999e+05     4.676663   482.303784          21.480126
std    3.235692e+06     4.906273   392.192230          12.105158
min    7.077310e+02     0.029411    45.552592           3.526316
25%    1.462125e+04     0.922769   257.139562          12.383953
50%    7.728386e+04     3.093346   368.415567          18.525960
75%    3.708446e+05     7.441195   586.972993          28.988324
max    3.064936e+07    37.106499  3343.454250          60.505780

       prot_area_perc           gdp   gni_per_cap
under_5_mort_rate  \
count     1700.000000  1.700000e+03   1700.000000        1700.000000

mean        12.201789  1.058568e+12   7898.668664          51.971955
```

```
std          9.116682  3.921323e+12  11592.516937            51.332162

min          0.000000  9.826326e+08     80.000000             3.200000

25%          5.839844  1.636221e+10    780.000000            10.000000

50%         10.293791  9.882942e+10   2150.770301            32.350000

75%         16.599298  4.122600e+11   9205.000000            79.925741

max         53.749825  5.580488e+13  58620.000000           239.100000


       pop_growth_perc           pop  urb_pop_growth_perc
urb_pop
count      1700.000000  1.700000e+03          1700.000000
1.700000e+03
mean          1.451313  3.060142e+08             2.252231
1.347903e+08
std           1.129312  9.482329e+08             1.642009
4.145755e+08
min          -2.397174  1.909812e+06            -2.757210
1.151309e+06
25%           0.630306  9.973065e+06             0.925308
5.469794e+06
50%           1.519890  2.689207e+07             2.315122
1.423239e+07
75%           2.276853  8.234386e+07             3.364747
4.835246e+07
max          11.180657  6.610030e+09            12.829046
3.264974e+09
```

3. Used feature/column abbreviations

The features/columns were given in Stage 1 clearer abbreviations in order to ensure easies understanding, representation and coding. These are listed in the following table together with the corresponding units:

---

4. Define the hypothesis to be investigated

The data series available can be summarized into the following country-specific parameter categories:

- various emissions of greenhouse gases such as CO2, CH4, N2O, others
- population-specific parameters: population count, urban population, population growth, etc.
- country economic indicators: GDP, GNI, Foreign Direct Investment, etc.

- land-related parameters: cereal yield, agricultural land, Nationally terrestrial protected areas, etc.
- climate data: precipitations, national disasters, etc.
- energy use
- counts of certain types of medical personnel
- etc.

The initial project goal of the project has already been defined during Stage 1:

Initial goal of the project: Analyze the relationships among the variable categories and evaluate the contribution of factors like country economy, energy use, land use, etc. on greenhouse gas emissions, precipitations, etc. Finally, develop a predictive machine learning model capable of predicting climate-related data or emissions from the other country-specific parameters.

Many of the features relating to climate data and emissions had to be removed in Stage 1 due to the big amount of missing values.

Without getting into much details here, it is generally considered that CO2 emissions are an important contributor to climate change. Taken for a certain country and year, these can be theoretically caused by energy use, country's population, economy, etc. Taking this and the available data into account, the hypothesis to be tested can be defined in more detail as follows:

The hypothesis to be tested: the CO2 emissions depend on the rest of the country-specific features available in the dataset such as energy use, various population metrics, GDP, FNI, cereal yield, etc. and can be predicted from these.

In this context, the CO2 emissions will be from now on treated as the Dependent Variable (DV) and I will investigate how/whether it depends on the other features/variables.

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5. Feature engineering

The available columns reveal that the features representing CO2 emissions and energy use have three different reference values:

- per capita: *co2_per_cap* and *en_per_cap*
- per unit of GDP: *co2_per_gdp* and *en_per_gdp*
- total values: *co2_ttl*

Since the energy use is not available as a total value, an additional column will be derived by multiplying the value referred to a unit of GDP *'en-er_gdp'* with the column *'gdp'* and dividing by 1000 (The energy use per unit of GDP is defined in the dataset documentation as the energy use in kilograms of oil equivalent per \$1000 of GDP [kg oil eq./\$1,000]).

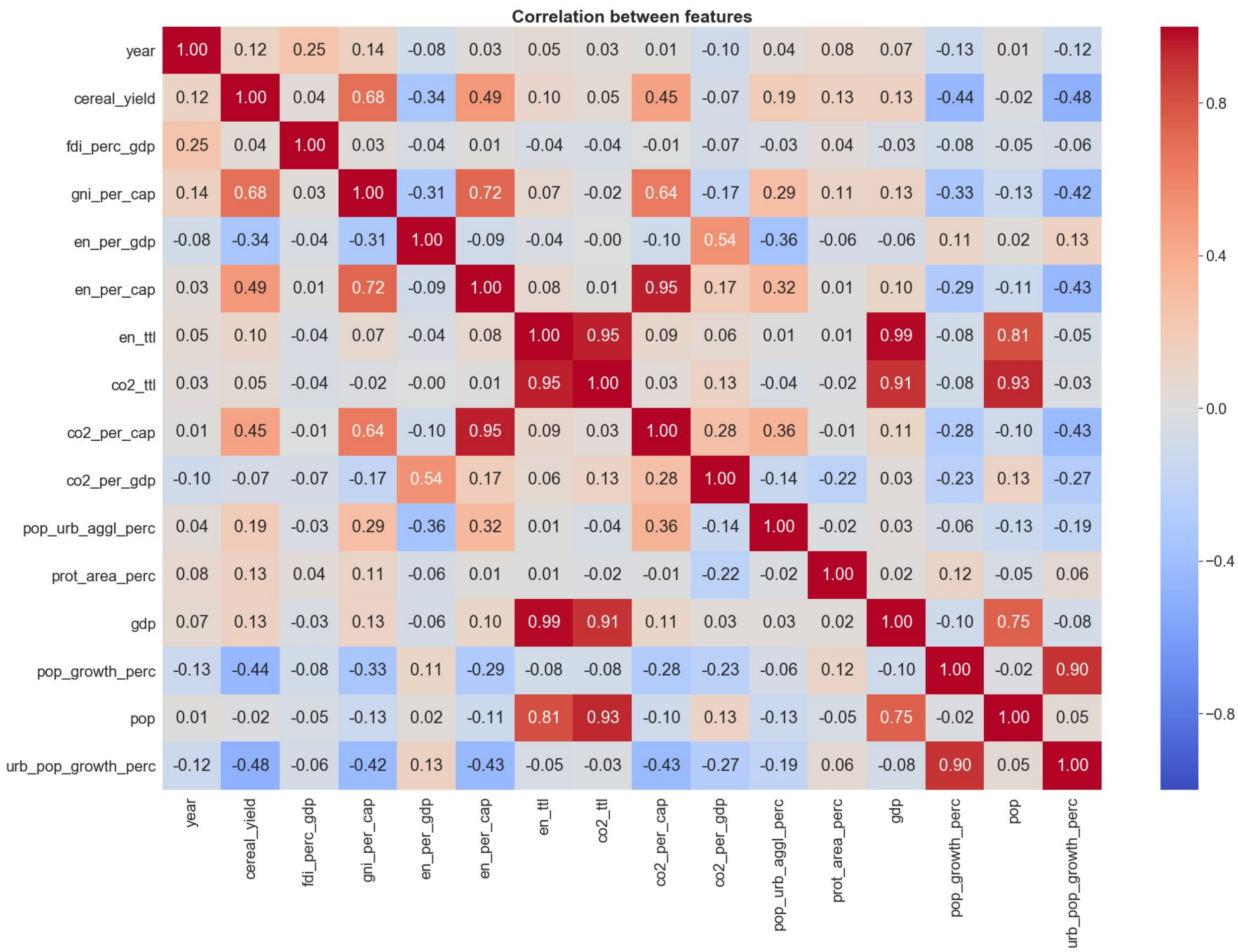
Create a column for the total energy use:

```
# create a column for the total energy use
data['en_ttl'] = data['en_per_gdp'] * data['gdp'] /1000
```

Choose the best unit/reference value for the CO2 emissions and the energy use

In order to select the best reference value to work with for the CO2 emissions and the energy use, their relationships with the other variables should be investigated. The aim here is to check which units allow for better correlation with the biggest amount of other features. This is done by examining the correlation matrix of all features:

```
# select all features
features_all =
data[['country','year','cereal_yield','fdi_perc_gdp','gni_per_cap',
'en_per_gdp', 'en_per_cap', 'en_ttl', 'co2_ttl', 'co2_per_cap',
'co2_per_gdp', 'pop_urb_aggl_perc', 'prot_area_perc', 'gdp',
'pop_growth_perc', 'pop', 'urb_pop_growth_perc']]

# plot a correlation of all features
# correlation matrix
sns.set(font_scale=2)
f,ax=plt.subplots(figsize=(30,20))
sns.heatmap(features_all.corr(), annot=True, cmap='coolwarm', fmt =
".2f", center=0, vmin=-1, vmax=1)
plt.title('Correlation between features', fontsize=25, weight='bold' )
plt.show()

sns.set(font_scale=1)
```



When comparing the dependencies of *co2_ttl*, *co2_per_cap* and *co2_per_gdp* with other features, *co2_per_cap* correlates with a bigger amount of other variables. It also represents the CO2 emissions independently of population size, making it more representative when analyzing and comparing the emissions of countries with different sizes and population counts.

Since the chosen variables are referred to the population count, it wouldn't make much sence to take the variable *pop* (indicating the population count) - this can be also seen from the weak correlation coefficient.

Taking this into account, the features *pop*, *en_per_gdp*, *en_ttl*, *co2_per_gdp*, *co2_ttl* will be removed from further analysis:

```
features =
features_all[['country','cereal_yield','fdi_perc_gdp','gni_per_cap',
'en_per_cap', 'co2_per_cap',
                        'pop_urb_aggl_perc', 'prot_area_perc', 'gdp',
'pop_growth_perc', 'urb_pop_growth_perc']]
```

6. Prepare the visualizations

Plotting preparation

Ensure easier labeling of the plots

In order to make the labeling of the variables within plots easier in the code, a dictionary with the column names and variable labels to use on axes is defined:

```
# a dictionary with feature labels
labels_dict = {'gni_per_cap':'GNI per capita [Atlas $]',
               'gdp':'Gross Domestic Product [$]',
               'cereal_yield':'Cereal yield [kg/ha]',
               'prot_area_perc': 'Nationally terrestrial protected
areas [% of total land area]',
               'fdi_perc_gdp': 'Foreign Direct Investment [% of GDP]',
               'pop_urb_aggl_perc': 'Population in urban
agglomerations > 1mln [%]',
               'urb_pop_growth_perc':'Urban population growth [annual
%]',
               'pop_growth_perc': 'Population growth [annual %]',
               'co2_per_cap':'CO2 emissions per capita [t]',
               'en_per_cap':'Energy use per capita [kg oil eq]' }
```

Choose a subset of countries to plot

The big amount of data points will result in slower processing of the plot and in a less clear representation. This can be avoided by choosing roughly half of the countries just for the paired scatter plot:

```
# select only rows for half of the countries chosen randomly in order
to ensure better visibility
chosen_countries=['LIC', 'LMC', 'LMY', 'MAR', 'MEX', 'MIC', 'MNA',
'MOZ', 'MYS',
'NGA', 'NLD', 'NZL', 'PAK', 'PAN', 'PER', 'PHL', 'PRT', 'PRY',
'ROM', 'SAS', 'SAU', 'SDN', 'SEN', 'SLV', 'SSA', 'SWE', 'SYR',
'TGO', 'THA', 'TUR', 'TZA', 'UMC', 'URY', 'USA', 'VEN', 'VNM',
'WLD', 'ZAF', 'ZAR', 'ZMB', 'ECA', 'POL', 'RUS', 'UKR', 'YEM',
'ETH', 'BEL']

features_chosen = features[features['country'].isin(chosen_countries)]
```

---

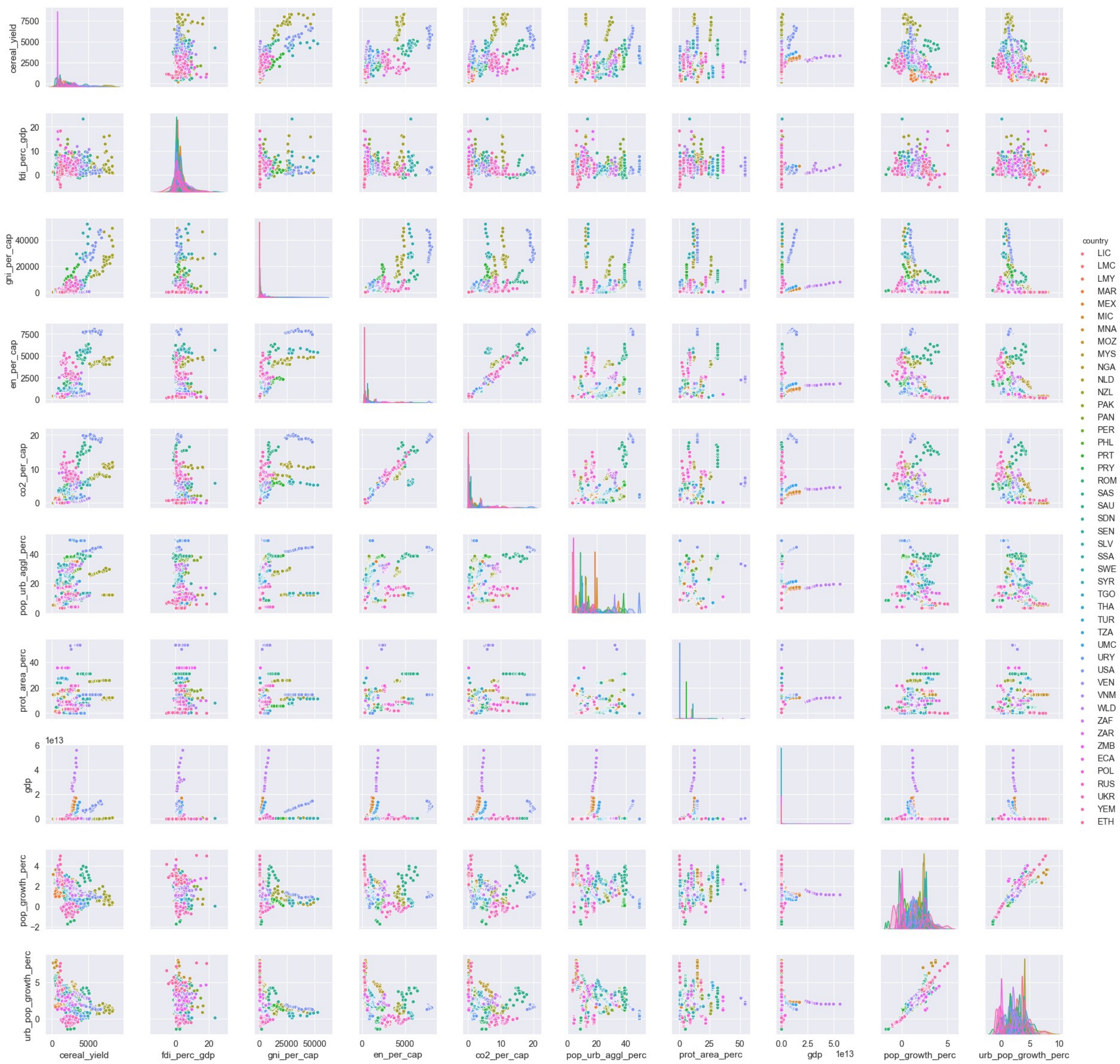
7. Create plots and visualizations

The visualization is organized in a way that global overview of the data and dependencies is presented first, followed by more and more detailed representations of the more relevant relationships.

7.1 A global look onto all relationships

Scatter plots of all chosen variables and countries will give a first impression of possible trends:

```
sns.set(font_scale=1.3)
sns.pairplot(data=features_chosen, hue='country')

<seaborn.axisgrid.PairGrid at 0x15f19f28>
```

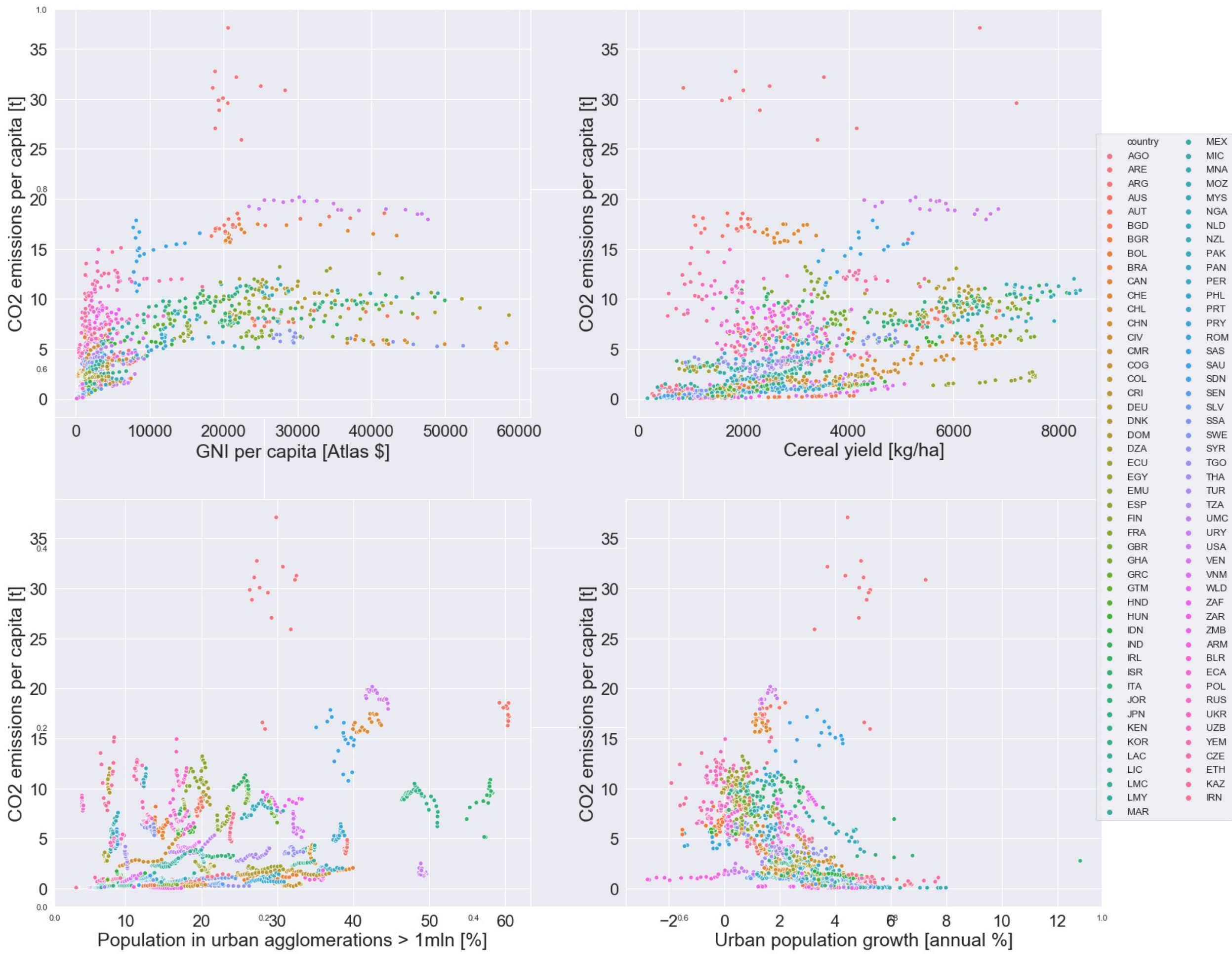


The most obvious linear dependency of co2_per_cap is with en_per_cap. Apparent hints for nonlinear relationships can be observed in the plots of *co2_per_cap* versus *gni*, *pop_urb_aggl_perc*, *pop_growth_perc*, *urb_pop_growth_perc*.

7.2 A closer look onto chosen plots

These dependencies will be explored in more detail for all available countries in the following plots:

```
# set default settings of the seaborn library
sns.set()

# plot all scatterplots

fig,ax=plt.subplots(figsize=(25,22))
#fig.subplots_adjust(hspace=0.1, wspace=0.1)
ind=1


# set color theme
sns.set_context("paper")
sns.set(color_codes=True, font_scale=2)

for [col, label] in [['gni_per_cap',labels_dict['gni_per_cap']],
['cereal_yield',labels_dict['cereal_yield']],
['pop_urb_aggl_perc',labels_dict['pop_urb_aggl_perc']],
['urb_pop_growth_perc',labels_dict['urb_pop_growth_perc']]]:

    ax = fig.add_subplot(2,2,ind)
    sns.scatterplot(ax=ax, x=col, y="co2_per_cap", data=features,
hue="country", legend='full')
    ax.legend_.remove()
    ax.set_xlabel(label, fontsize=25)
    ax.set_ylabel(labels_dict['co2_per_cap'], fontsize=25)
    ind+=1

# create common legend
handles, labels = ax.get_legend_handles_labels()
fig.legend(handles, labels, ncol=2, loc='center right', fontsize=13)
plt.show()
```



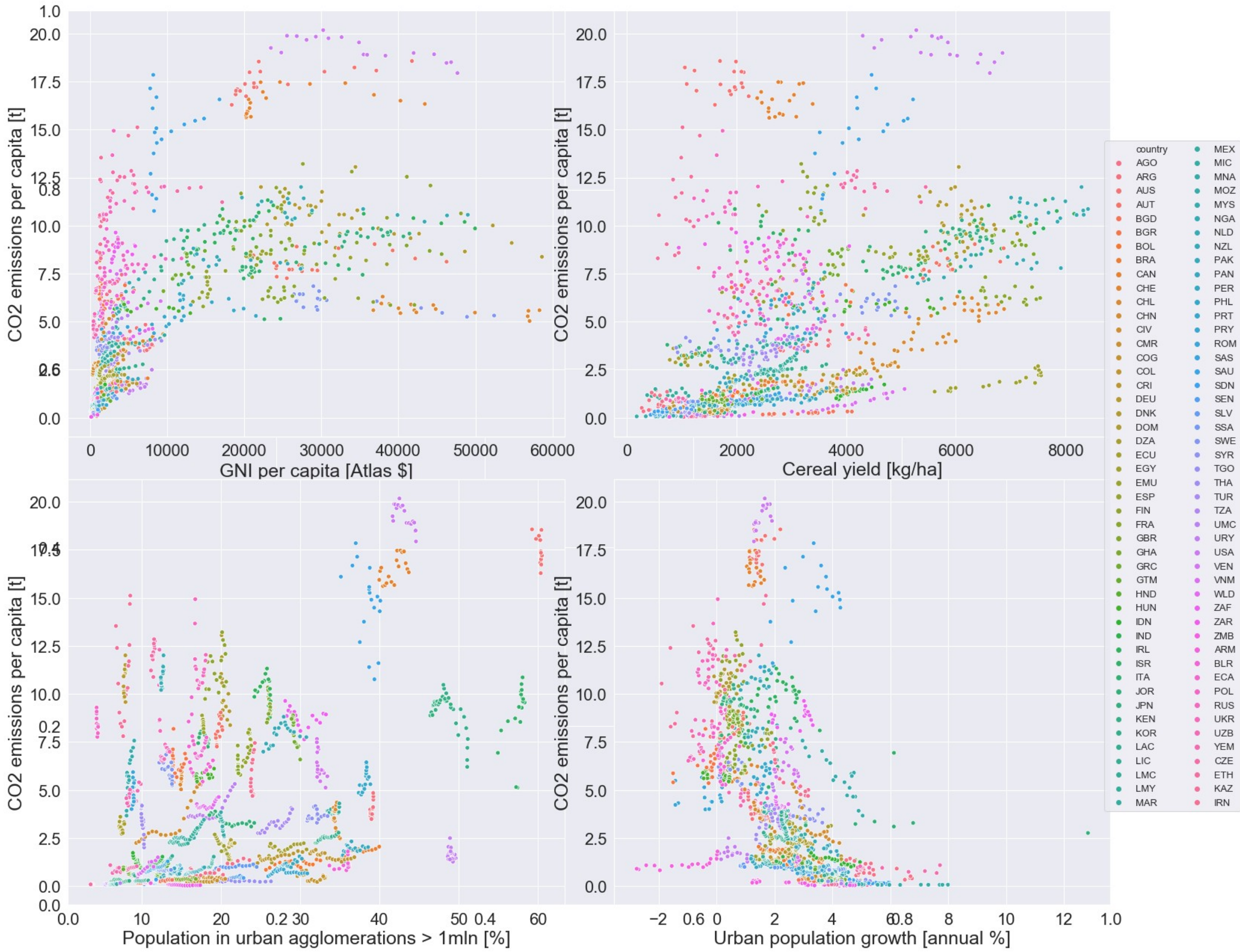
As a whole, all four diagrams exhibit not only local tendencies for each country (in most cases at least), which are similar, but also global trends for all data points. Worth noticing is also that these trends are nonlinear, but with different structure in all plots, implying different kinds of theoretical contribution to the DV CO2 emissions per capita. This could be a valuable asset for the future prediction of the DV.

Outliers

Another aspect that draws the attention is the group of outlier points of the same tome of orange for the range of CO2 emissions per capita between *25t* and *40t*. All of these belong to the data series corresponding to the country of United Arab Emirates (country code *ARE*). Other outliers corresponding to certain countries (same color) can also be identified, which do not disturb the global trends that much though. After removing the rows corresponding to *ARE*, the plots look as follows:

```
# remove the ARE outliers
features = features[features['country']!="ARE"]

# plot all scatterplots

fig,ax=plt.subplots(figsize=(25,22))
```

```
fig.subplots_adjust(hspace=0.1, wspace=0.1)
ind=1

# set color theme
sns.set_context("paper")
sns.set(color_codes=True, font_scale=2)

for [col, label] in [['gni_per_cap',labels_dict['gni_per_cap']],
['cereal_yield',labels_dict['cereal_yield']],
['pop_urb_aggl_perc',labels_dict['pop_urb_aggl_perc']],
['urb_pop_growth_perc',labels_dict['urb_pop_growth_perc']]]:
    ax = fig.add_subplot(2,2,ind)
    sns.scatterplot(ax=ax, x=col, y="co2_per_cap", data=features,
hue="country", legend='full')
    ax.legend_.remove()
    ax.set_xlabel(label, fontsize=25)
    ax.set_ylabel(labels_dict['co2_per_cap'], fontsize=25)
    ind+=1

# create common legend
handles, labels = ax.get_legend_handles_labels()
fig.legend(handles, labels, ncol=2, loc='center right', fontsize=13)
plt.show()
```

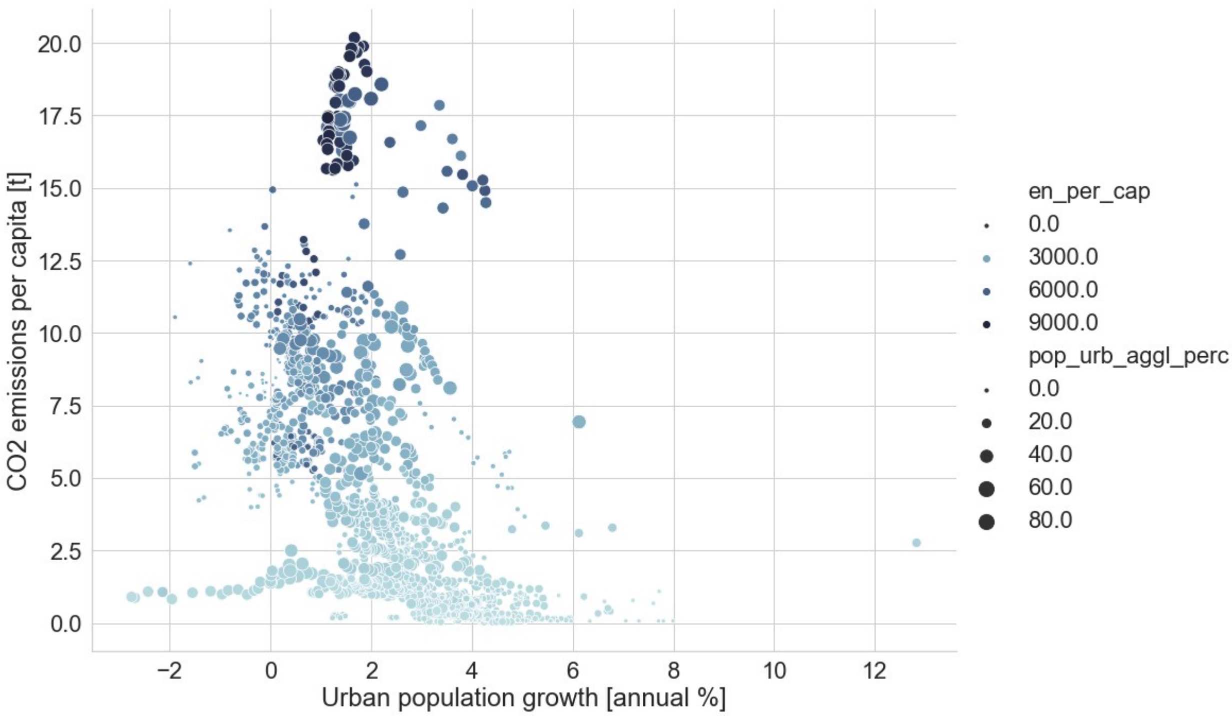


After removing the outliers of a single country, the trends have become even more visible.

The following plot shows the relationsip between 4 variables:

```
# 4d plot

sns.set(style="whitegrid", font_scale=2)

cmap = sns.cubehelix_palette(rot=-.2, as_cmap=True)
g = sns.relplot(
    data=features,
    x="urb_pop_growth_perc", y="co2_per_cap",
    hue="en_per_cap", size="pop_urb_aggl_perc",
    palette=cmap, sizes=(10, 200),
    height=10, aspect= 4/3
)

g.ax.set_xlabel(labels_dict['urb_pop_growth_perc'])
g.ax.set_ylabel(labels_dict['co2_per_cap'])
```

```
Text(78.37033880208335, 0.5, 'CO2 emissions per capita [t]')
```



8. Visualization conclusions

Valuable insights have been gained through targeted plotting of relevant dependencies for the further predictive analysis:

- The variables representing CO2 emissions and energy use both referred to the population count (per capita) are related to more features and are taken for further analysis.
- The population count feature is therefore not useful any more and removed.
- The CO2 emissions per capita exhibit strong linear dependency on energy use and show nonlinear relationships with other variables.
- In most cases are visible not only local trends for each single country but also global trends for all observations. The global trends can in certain cases be divided into multiple data point paths for certain groups of countries or clusters of countries.
- Groups of outliers with the same colors corresponding to certain countries have been detected. The group that stands out the most from the global trends origins from the data series on the United Arab Emirates (country code *ARE*). This can additionally be considered during data selection for the predictive analysis.
- The pronounced nonlinear character of the majority of dependencies as well as the clustered points of certain countries are indications against some and in favour of other machine learning algorithms for the predictive analysis. This would suggest the use of algorithms capable to handle nonlinearities and groups of points easily (e.g. Random Forest), rather than algorithms designed to describe linear relationships (e.g. Linear Regression).