

Capstone 2 Project

Global CO2 Emissions Prediction

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Springboard – May 2021



Introduction

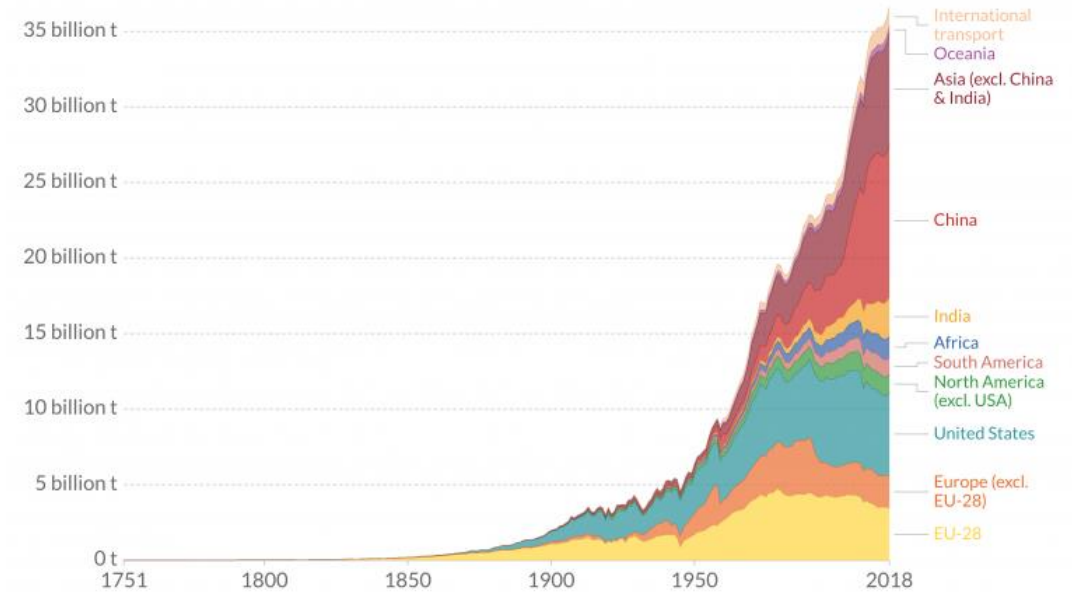
❖ Problem Statement

- The growth of CO₂ emissions is a major contributing factor to the speed of climate change.
- Since 1970, CO₂ emissions have increased by about 90%,.
- In order to prioritize which initiative has the highest impact on reducing CO₂ emissions, governments and industries must be equipped with high-performing, predictive tools for future emissions.

❖ Key Stakeholders

- Politics and policies: ministries, departments, agencies, and directions of national governments;
- Research and education: universities, institutes, research centers, laboratories;
- Supply and demand: industrial companies related to energy, food, air, equipment manufacturing, etc.;
- Organizations, societies, and influencers related to energy, environment, health, etc.

Annual total CO₂ emissions, by world region



Source: Carbon Dioxide Information Analysis Center (CDIAC); Global Carbon Project (GCP)
Note: 'Statistical differences' included in the GCP dataset is not included here.
OurWorldInData.org/co2-and-other-greenhouse-gas-emissions • CC BY

Data Preprocessing

❖ Data Overview

- The CO2 and Greenhouse Gas Emissions dataset is a collection of key metrics maintained by Our World in Data. It includes data on CO2 emissions (annual, per capita, cumulative and consumption-based), other greenhouse gases, energy mix, and other relevant metrics of different countries from the year 1750 - 2019.
- The data set of agriculture and food production are sourced from UNDATA containing the information on agricultural land use and beef production of different countries from the year 1750 - 2019.

```
co2_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23708 entries, 0 to 23707
Data columns (total 7 columns):
#   Column                                Non-Null Count  Dtype
---  ---                                -
0   iso_code                             20930 non-null object
1   country                             23708 non-null object
2   year                                23708 non-null int64
3   annual_co2_prod_Megaton              23170 non-null float64
4   primary_energy_consumption_10Gwh     6044 non-null float64
5   population                           21071 non-null float64
6   gdp                                  13002 non-null float64
dtypes: float64(4), int64(1), object(2)
memory usage: 1.3+ MB
```



```
agri_land_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14378 entries, 0 to 14377
Data columns (total 4 columns):
#   Column                                Non-Null Count  Dtype
---  ---                                -
0   Country or Area                       14377 non-null object
1   Year                                  14369 non-null float64
2   Unit                                  14369 non-null object
3   Value_agri_1000hectare                14369 non-null float64
dtypes: float64(2), object(2)
memory usage: 449.4+ KB
```

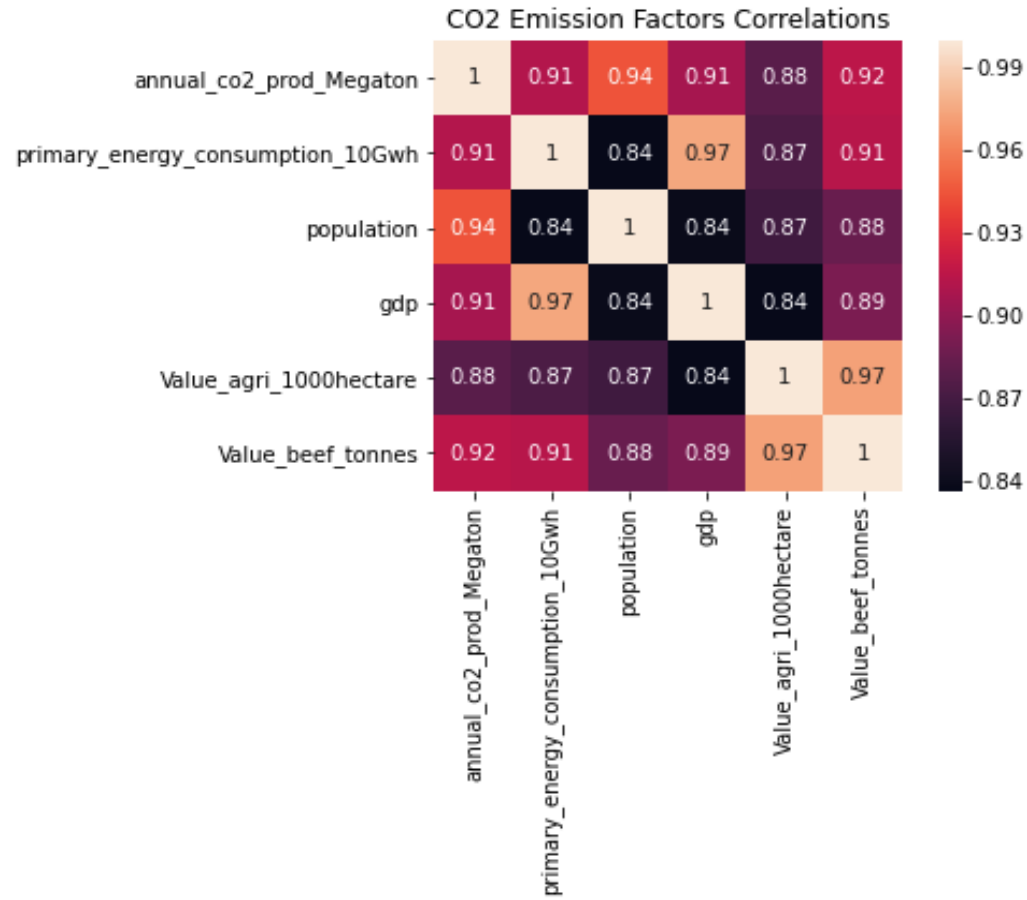


```
beef_prod_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13197 entries, 0 to 13196
Data columns (total 4 columns):
#   Column                                Non-Null Count  Dtype
---  ---                                -
0   Country or Area                       13196 non-null object
1   Year                                  13194 non-null float64
2   Unit                                  13194 non-null object
3   Value_beef_tonnes                    13194 non-null float64
dtypes: float64(2), object(2)
memory usage: 412.5+ KB
```

Data Preprocessing

❖ Data Analysis

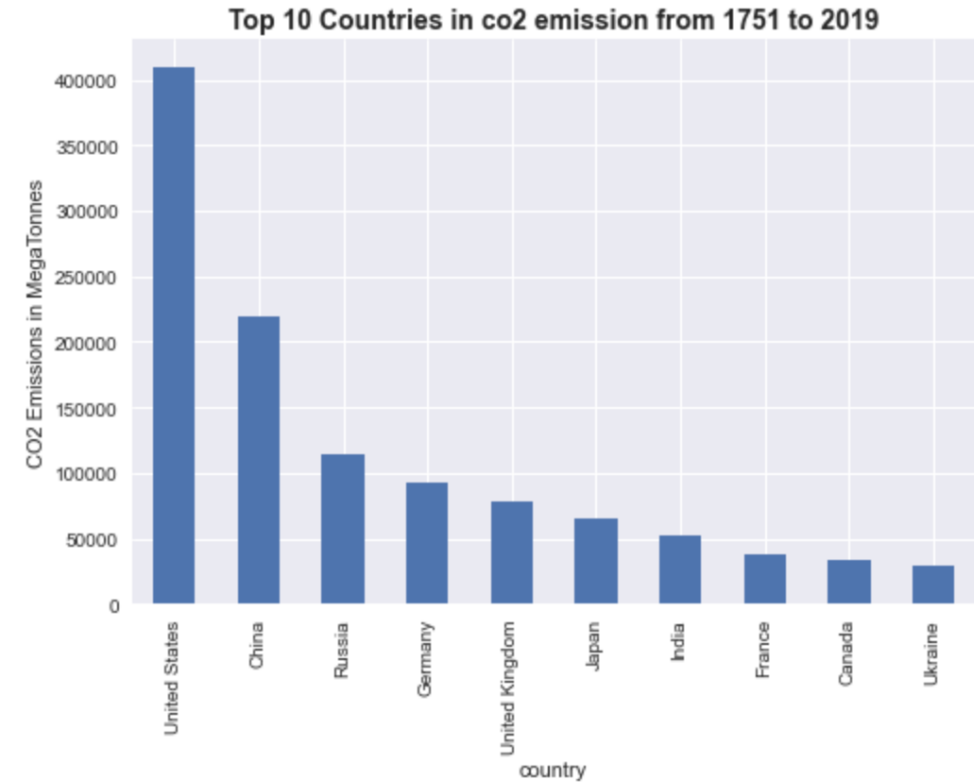
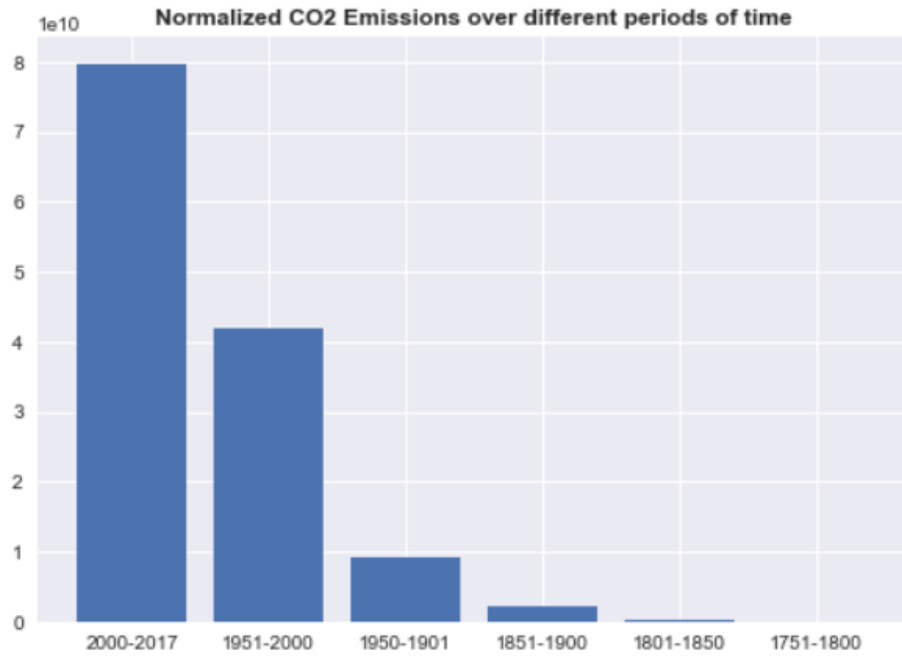


Annual CO2 production has the strong correlation with:

- population (0.94)
- beef production (0.92)
- primary energy consumption and GDP (0.91)

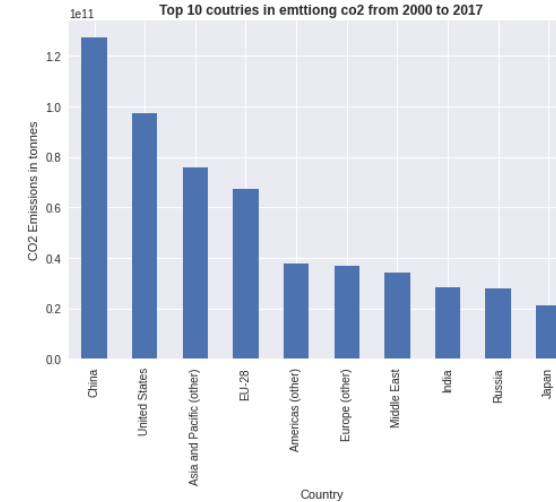
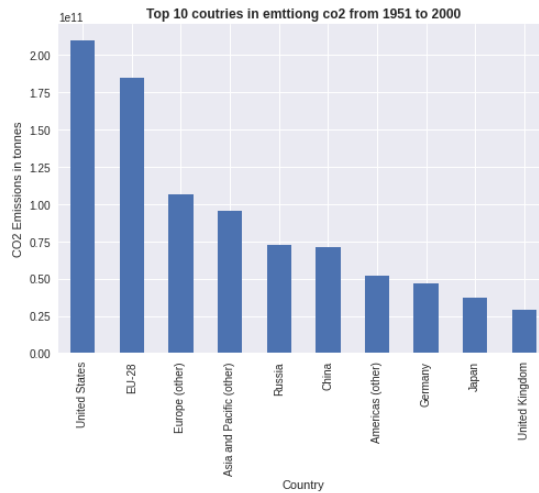
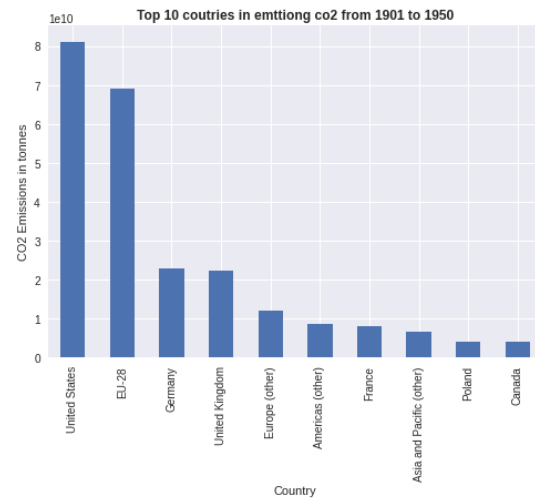
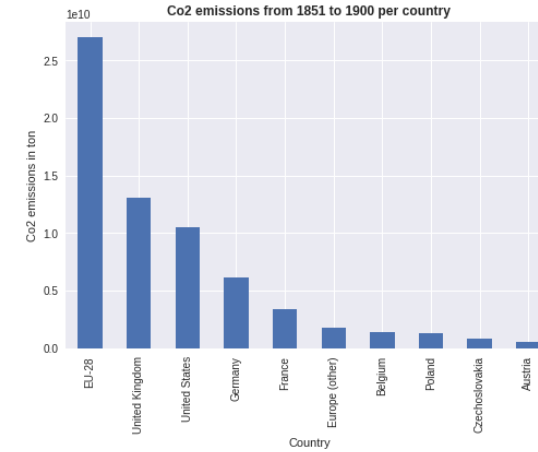
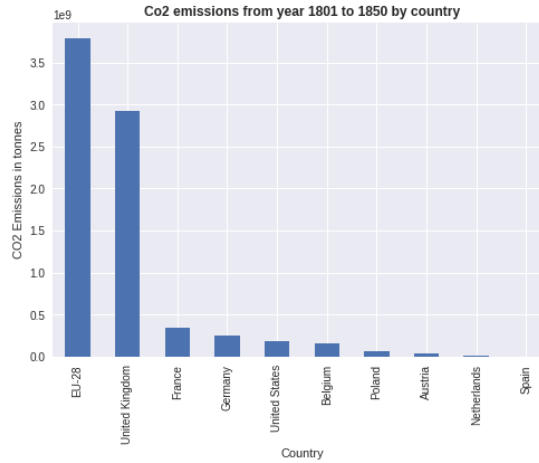
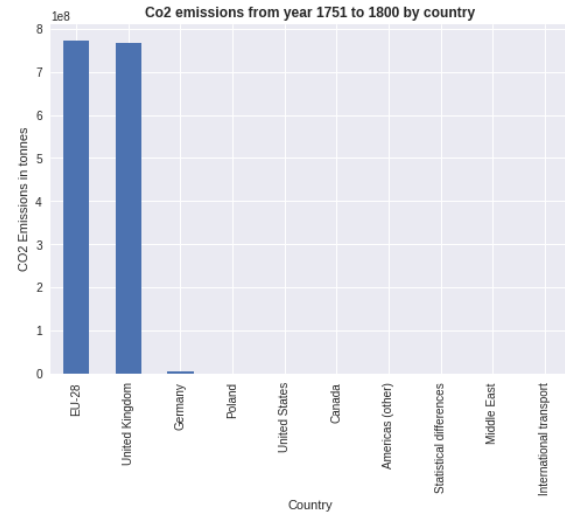
Data Preprocessing

❖ Data Analysis



Data Preprocessing

❖ Data Analysis



Data Preprocessing

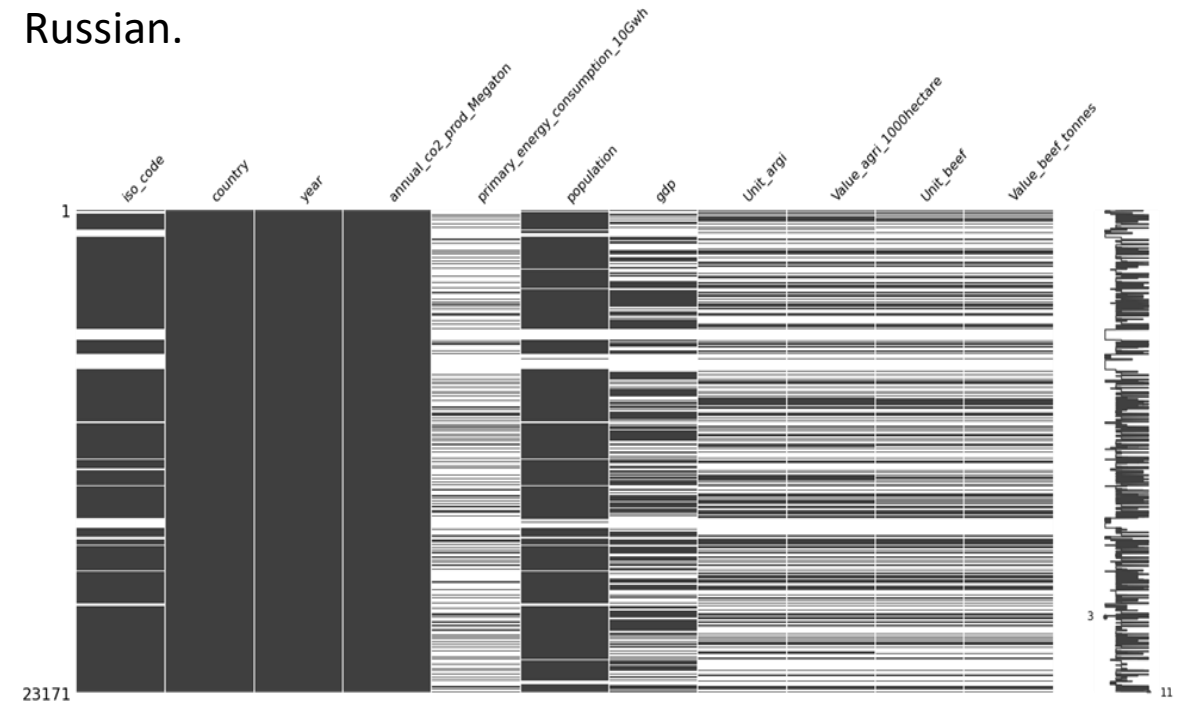
❖ Featuring Engineering

Selected Features

- iso_code: categorical feature.
- country: categorical feature.
- Year: date/time feature
- annual_co2_prod_Megaton: numerical feature.
- primary_energy_consumption_10Gwh: numerical feature.
- Population: numerical feature.
- Gdp: numerical feature.
- Value_agri_1000hectare: numerical feature.
- Value_beef_tonnes: numerical feature.

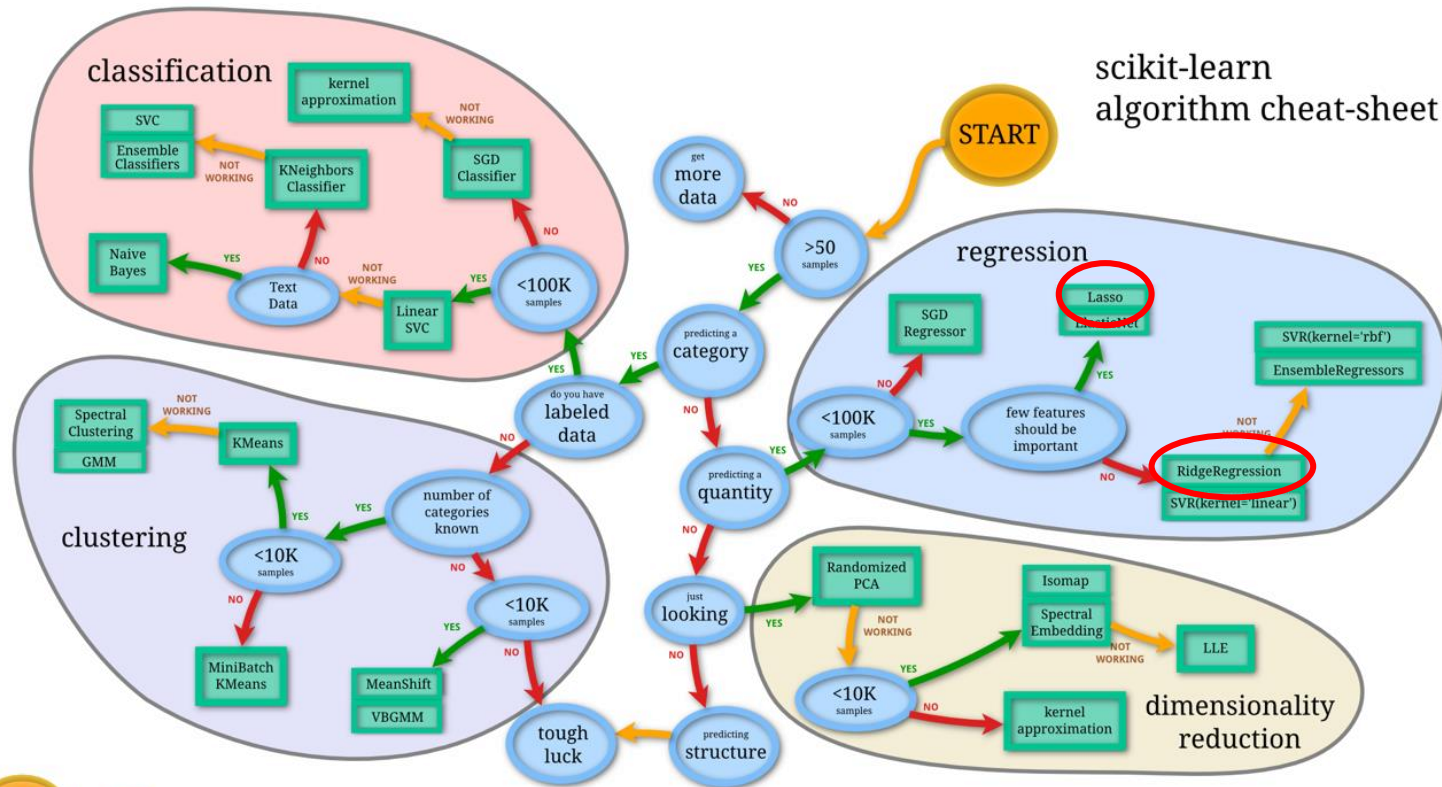
Processing

- NaN data: “fillna” to be replaced by the value of 0
- Thresholds: primary energy > 70k and 110k
- Region names: Africa, Europe, USA, China, India, and Russian.



Modeling

❖ Model Selection



❖ Linear Regression

```
# train the model
ml_fea_5 = LinearRegression(fit_intercept=True, normalize=True)
ml_fea_5.fit(x_fea_5_train,y_fea_5_train)
```

❖ Lasso Regression

```
lasso_rgns = Lasso(alpha=alp,
                    fit_intercept=True,
                    normalize=True,
                    selection='cyclic',
                    max_iter=10000,
                    tol=0.0001,
                    warm_start=False)
```

❖ Ridge Regression

```
for alp in alpha_space:
    ridge_rgns = Ridge(alpha=alp,
                       fit_intercept=True,
                       normalize=True)
```



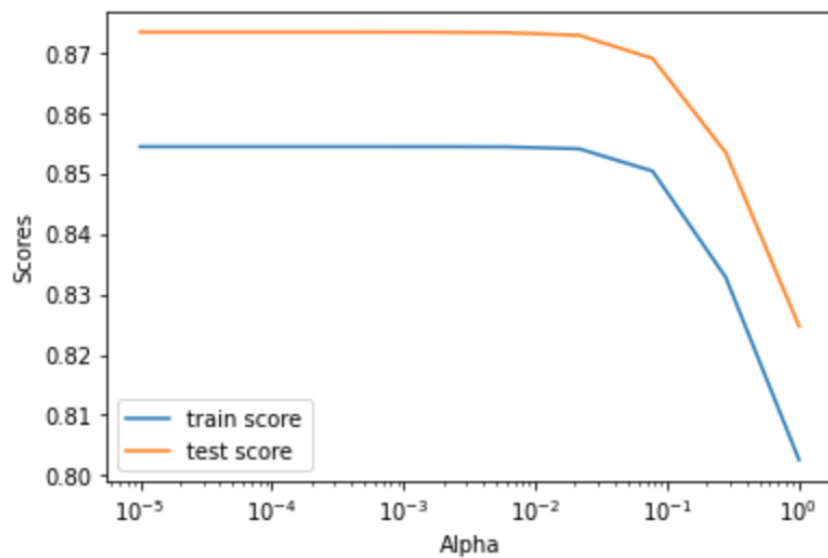
(https://scikit-learn.org/stable/tutorial/machine_learning_map/index.html)

Results and Discussions

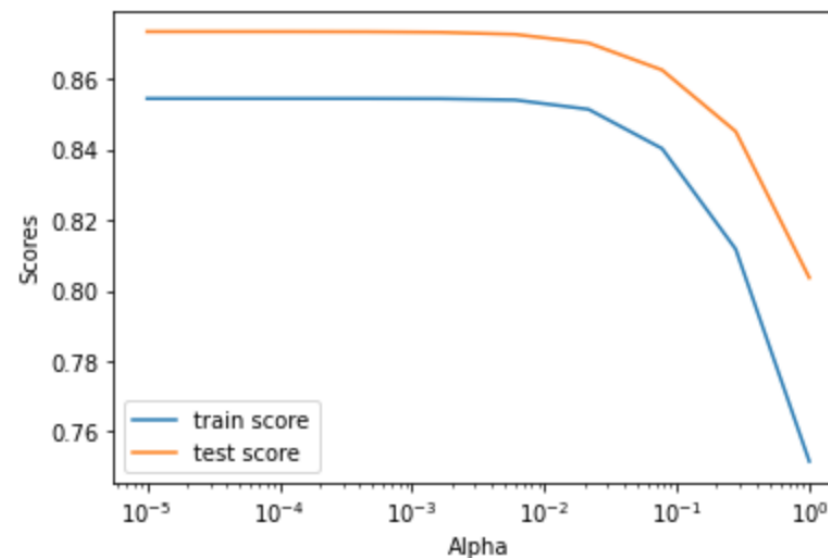
❖ Hypertable

Rank	r2_train	rmse_train	r2_test	rmse_test ↓	alpha	incpt	description
1	0.8544	554.3107	0.8734	581.6483	0.00E+00	-532.32	Linear
2	0.8544	554.3107	0.8734	581.6486	1.00E-05	-532.30	Lasso
3	0.8544	554.3107	0.8734	581.6493	3.60E-05	-532.26	Lasso
4	0.8544	554.3107	0.8734	581.6508	1.00E-05	-532.31	Ridge
5	0.8544	554.3107	0.8734	581.6520	1.29E-04	-532.11	Lasso

❖ Lasso Regression

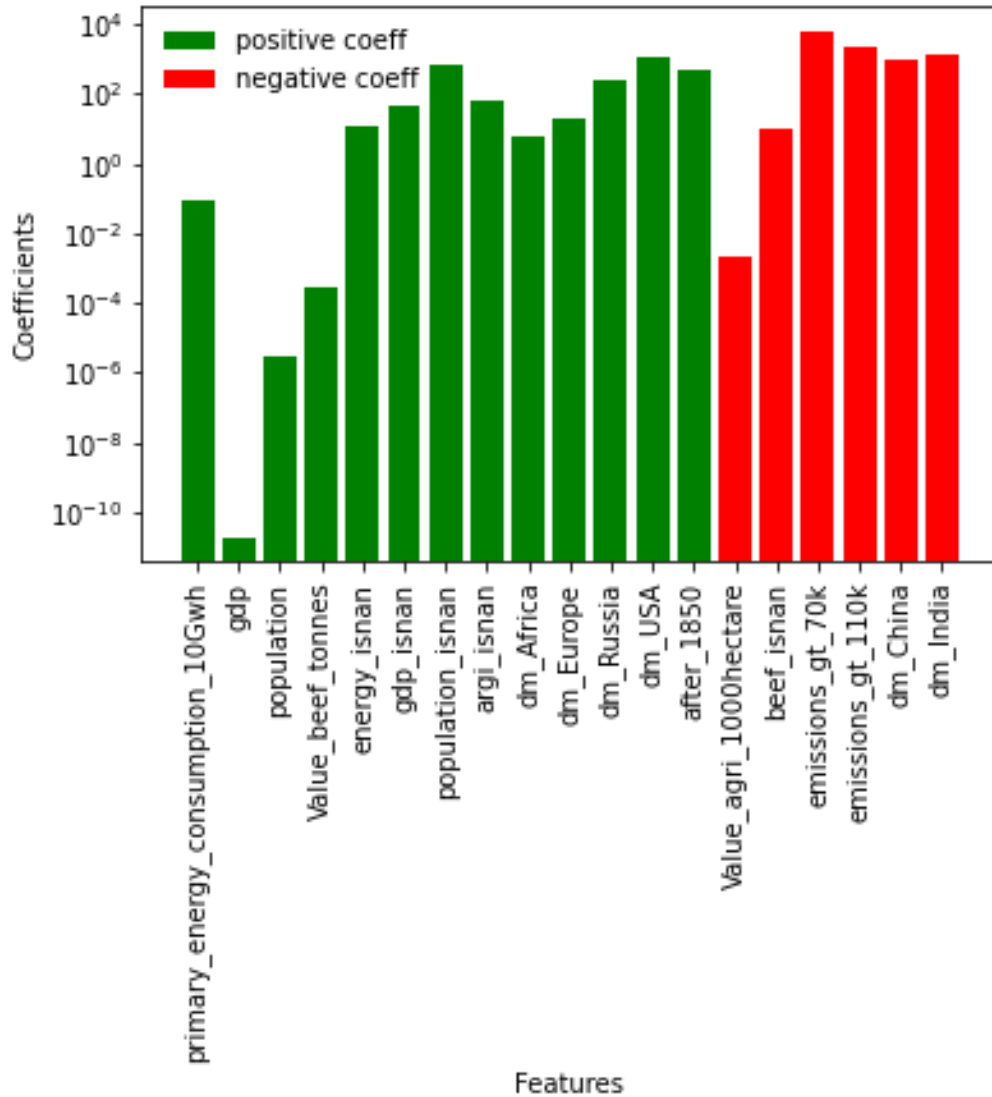


❖ Ridge Regression



Results and Discussions

❖ Coefficients



Observations

- CO2 emission is positively related to primary energy consumption, GDP, population, and beef production, but reversely related to agriculture land use.
- United States, Europe, Russian, and Africa contributions are positively related to CO2 emission, but China and India are negatively related to CO2 emission.
- The possible explanation can be:
 - Low contribution of CO2 emission per person of China and India due to huge population in these two countries causes low per capita CO2 emission.
 - China and India have larger agriculture land use and less beef production.

Conclusions

- ❖ This work investigated CO2 emissions by considering five main factors, including primary energy consumption, GDP, population, agriculture land use, and beef production.
- ❖ Three machine learning regression models (linear, Lasso, and Ridge) are applied to the training and test data set in order to predict CO2 emission.
- ❖ The results show that multivariate linear regression is the best performance model for this data set.
- ❖ The coefficients of each feature show that CO2 emission is positively related to primary energy consumption, GDP, population, and beef production but agriculture land use has a negative effect on CO2 emission.
- ❖ The dummy variable coefficients show that United States, Europe, Russian, and Africa contributions are positively related to CO2 emission, but China and India are negatively related to CO2 emission.
- ❖ **Future works:**
 - Add geological features based on the location of countries.
 - Add temporal features based on time period.
 - Standardize the features. It is important to standardize the features by removing the mean and scaling to unit variance.
 - Consider extra ML/AI models, including NLP and ANN.