Global Carbon Emission Comparisons

Group 15 - Ruchita, Avneesh, Tarini, Kobe, Mikhail

Topic Description

- Alarming rates of carbon emissions
- Study major factors affecting climate conditions
- Analyze correlations between energy usage and GHG emissions through transportation
- Determine the recent impact of alternative energy sources
- Predict future impact of higher alternative energy adoption

Group Roles

- X - Avneesh
- Triangle - Tarini
- Circle - Mikhail
- Square - Ruchita & Kobe

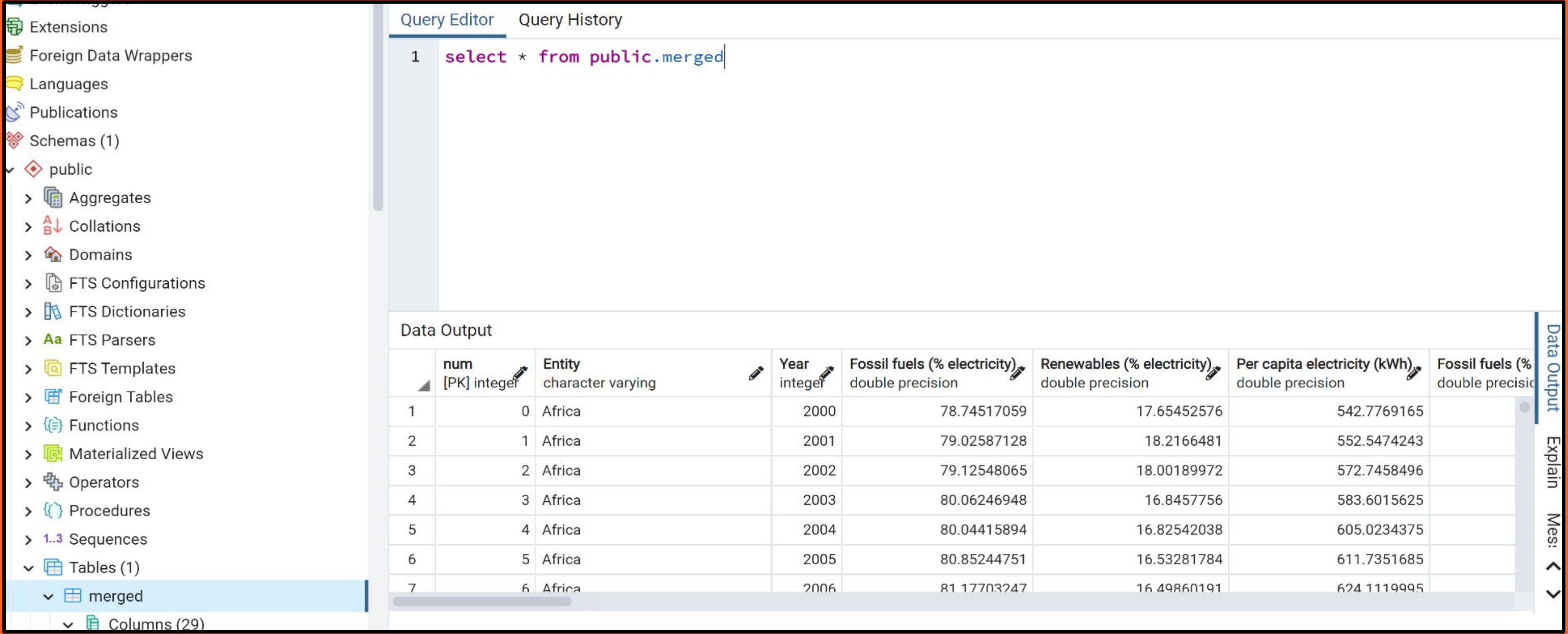
Data Description

- Annual worldwide vehicle mix by different energy types (Diesel, Electric, Hybrid, etc.)
- Overall GHG emissions by sector
- Market demand of all vehicles types
- Energy production

Database

- Downloaded datasets related to co2 emissions and GHG emissions
  - Source - https://ourworldindata.org/
- Tried to find the unique key to merge the data in this case it is the country name and year
- Collected the datasets for Transport Vehicle demand country wise and year wise, merged it with the GHG emissions database

Database Sample



Machine Learning Model Summary

OLS Regression Results

Dep. Variable:	ev_savings	**R-squared (uncentered):**	0.507
Model:	OLS	**Adj. R-squared (uncentered):**	0.493
Method:	Least Squares	**F-statistic:**	36.02
Date:	Thu, 01 Sep 2022	**Prob (F-statistic):**	2.36e-75
Time:	03:50:38	**Log-Likelihood:**	-8982.0
No. Observations:	576	**AIC:**	1.800e+04
Df Residuals:	560	**BIC:**	1.807e+04
Df Model:	16		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Fossil fuels (% equivalent primary energy)	7950.8993	5231.081	1.520	0.129	-2324.038	1.82e+04
Transport_x	0.1986	0.161	1.234	0.218	-0.118	0.515
Agriculture	0.0011	0.001	1.013	0.312	-0.001	0.003
Land-use change and forestry	0.0015	0.001	2.731	0.007	0.000	0.003
Waste	0.0082	0.005	1.731	0.084	-0.001	0.018
Industry	0.0584	0.005	10.943	0.000	0.048	0.069
Manufacturing and construction	-0.0240	0.002	-11.381	0.000	-0.028	-0.020
Transport_y	-0.1989	0.155	-1.280	0.201	-0.504	0.106
Electricity and heat	0.0080	0.001	7.096	0.000	0.006	0.010
Buildings	-0.0098	0.003	-3.043	0.002	-0.016	-0.003
Fugitive emissions	-0.0062	0.002	-3.892	0.000	-0.009	-0.003
Other fuel combustion	0.0040	0.016	0.246	0.805	-0.028	0.036
Aviation and shipping	-0.0209	0.006	-3.501	0.001	-0.033	-0.009
Renewables (% equivalent primary energy)	5839.8990	1.32e+04	0.444	0.657	-2e+04	3.17e+04
Fossil fuels (% electricity)	-1.103e+04	5700.997	-1.935	0.054	-2.22e+04	168.776
Renewables (% electricity)	-4951.9647	9257.701	-0.535	0.593	-2.31e+04	1.32e+04

Renewables (% equivalent primary energy)	5839.8990	1.32e+04	0.444	0.657	-2e+04	3.17e+04
Fossil fuels (% electricity)	-1.103e+04	5700.997	-1.935	0.054	-2.22e+04	168.776
Renewables (% electricity)	-4951.9647	9257.701	-0.535	0.593	-2.31e+04	1.32e+04

Omnibus:	416.999	**Durbin-Watson:**	1.018
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	21995.226
Skew:	2.579	**Prob(JB):**	0.00
Kurtosis:	32.831	**Cond. No.**	2.41e+08

Notes:
[1] R^2 is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[3] The condition number is large, 2.41e+08. This might indicate that there are
strong multicollinearity or other numerical problems.

Machine Learning Model - Data columns

```
Index([                            ('Petrol', 'Econ'),
                                    ('Petrol', 'Mid'),
                                    ('Petrol', 'Lux'),
                               ('Adv Petrol', 'Econ'),
                                ('Adv Petrol', 'Mid'),
                                ('Adv Petrol', 'Lux'),
                                   ('Diesel', 'Econ'),
                                    ('Diesel', 'Mid'),
                                    ('Diesel', 'Lux'),
                               ('Adv Diesel', 'Econ'),
                                ('Adv Diesel', 'Mid'),
                                ('Adv Diesel', 'Lux'),
                                      ('CNG', 'Econ'),
                                       ('CNG', 'Mid'),
                                       ('CNG', 'Lux'),
                                   ('Hybrid', 'Econ'),
                                    ('Hybrid', 'Mid'),
                                    ('Hybrid', 'Lux'),
                                 ('Electric', 'Econ'),
                                  ('Electric', 'Mid'),
                                  ('Electric', 'Lux'),
                                    ('Bikes', 'Econ'),
                                     ('Bikes', 'Lux'),
                        ('Electric Bikes', 'Adv Econ'),
                         ('Electric Bikes', 'Adv Lux'),
       'Fossil fuels (% equivalent primary energy)',
                                       'Transport_x',
                                       'Agriculture',
                         'Land-use change and forestry',
                                             'Waste',
                                          'Industry',
                       'Manufacturing and construction',
                                       'Transport_y',
                               'Electricity and heat',
                                         'Buildings',
                                'Fugitive emissions',
                               'Other fuel combustion',
                               'Aviation and shipping',
         'Renewables (% equivalent primary energy)',
                         'Fossil fuels (% electricity)',
                           'Renewables (% electricity)',
                                     'fossil_demand',
                                         'ev_demand',
```

- To calculate CO2 emissions saved by electric vehicles year by year
- Features given in the screenshot are taken into consideration

Machine Learning Model Output

```
[121] X = df_ev_ghg_merged[[
          'Fossil fuels (% equivalent primary energy)',
      'Transport_x',
      'Agriculture',
      'Land-use change and forestry',
      'Waste', 'Industry', 'Manufacturing and construction', 'Transport_y',
      'Electricity and heat',
      'Buildings', 'Fugitive emissions', 'Other fuel combustion', 'Aviation and shipping', 'Renewables (% equivalent primary energy)', 'Fossil fuels (% electricity)',
      'Renewables (% electricity)']]

[122] X

      y = df_ev_ghg_merged[['ev_savings']]

[124] lm = linear_model.LinearRegression()
      model = lm.fit(X,y)

      y_predictions = lm.predict(X)

[126] lm.score(X,y)

      0.4954363469172296
```

Next Steps...

- Explore and analyze data to study the impact of various vehicles by energy type on carbon emission
- Determine if there is a significant correlation between each factor
- Reveal possible outcomes of alternate energy consumption on carbon & GHG emissions
- Summarize each step taken in the machine learning preprocess