In [1]:

```
import numpy as np
import pandas as pd
import sqlite3
# !pip install ipython-sql # for sql magic abilities, i.e. %%sql, etc.
import IPython
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
df = pd.read_csv( '/Users/travis/Desktop/ADS-502/factbook.csv', sep=';'
list(df)
```

Out[2]:
```
['Country',
 'Area(sq km)',
 'Birth rate(births/1000 population)',
 'Current account balance',
 'Death rate(deaths/1000 population)',
 'Debt - external',
 'Electricity - consumption(kWh)',
 'Electricity - production(kWh)',
 'Exports',
 'GDP',
 'GDP - per capita',
 'GDP - real growth rate(%)',
 'HIV/AIDS - adult prevalence rate(%)',
 'HIV/AIDS - deaths',
 'HIV/AIDS - people living with HIV/AIDS',
 'Highways(km)',
 'Imports',
 'Industrial production growth rate(%)',
 'Infant mortality rate(deaths/1000 live births)',
 'Inflation rate (consumer prices)(%)',
 'Internet hosts',
 'Internet users',
 'Investment (gross fixed)(% of GDP)',
 'Labor force',
 'Life expectancy at birth(years)',
 'Military expenditures - dollar figure',
 'Military expenditures - percent of GDP(%)',
 'Natural gas - consumption(cu m)',
 'Natural gas - exports(cu m)',
 'Natural gas - imports(cu m)',
 'Natural gas - production(cu m)',
 'Natural gas - proved reserves(cu m)',
 'Oil - consumption(bbl/day)',
 'Oil - exports(bbl/day)',
 'Oil - imports(bbl/day)',
 'Oil - production(bbl/day)',
 'Oil - proved reserves(bbl)',
 'Population',
 'Public debt(% of GDP)',
 'Railways(km)',
 'Reserves of foreign exchange & gold',
 'Telephones - main lines in use',
 'Telephones - mobile cellular',
 'Total fertility rate(children born/woman)',
 'Unemployment rate(%)']
```

In [3]:
```
#clean up column names, stripping them of extra spaces
df.columns = (df.columns.str.strip().str.replace('-', '').str.replace('
list(df)
```

Out[3]:
```
['Country',
 'Area(sq_km)',
 'Birth_rate(births/1000_population)',
 'Current_account_balance',
 'Death_rate(deaths/1000_population)',
 'Debt_external',
 'Electricity_consumption(kWh)',
 'Electricity_production(kWh)',
 'Exports',
 'GDP',
 'GDP_per_capita',
 'GDP_real_growth_rate(%)',
 'HIV/AIDS_adult_prevalence_rate(%)',
 'HIV/AIDS_deaths',
 'HIV/AIDS_people_living_with_HIV/AIDS',
 'Highways(km)',
 'Imports',
 'Industrial_production_growth_rate(%)',
 'Infant_mortality_rate(deaths/1000_live_births)',
 'Inflation_rate_(consumer_prices)(%)',
 'Internet_hosts',
 'Internet_users',
 'Investment_(gross_fixed)(%_of_GDP)',
 'Labor_force',
 'Life_expectancy_at_birth(years)',
 'Military_expenditures_dollar_figure',
 'Military_expenditures_percent_of_GDP(%)',
 'Natural_gas_consumption(cu_m)',
 'Natural_gas_exports(cu_m)',
 'Natural_gas_imports(cu_m)',
 'Natural_gas_production(cu_m)',
 'Natural_gas_proved_reserves(cu_m)',
 'Oil_consumption(bbl/day)',
 'Oil_exports(bbl/day)',
 'Oil_imports(bbl/day)',
 'Oil_production(bbl/day)',
 'Oil_proved_reserves(bbl)',
 'Population',
 'Public_debt(%_of_GDP)',
 'Railways(km)',
 'Reserves_of_foreign_exchange_&_gold',
 'Telephones_main_lines_in_use',
 'Telephones_mobile_cellular',
 'Total_fertility_rate(children_born/woman)',
 'Unemployment_rate(%)']
```

In [4]:
```
# SQL database connection
cnn = sqlite3.connect('df.db')
print('...database connection created')
```

```
...database connection created
```

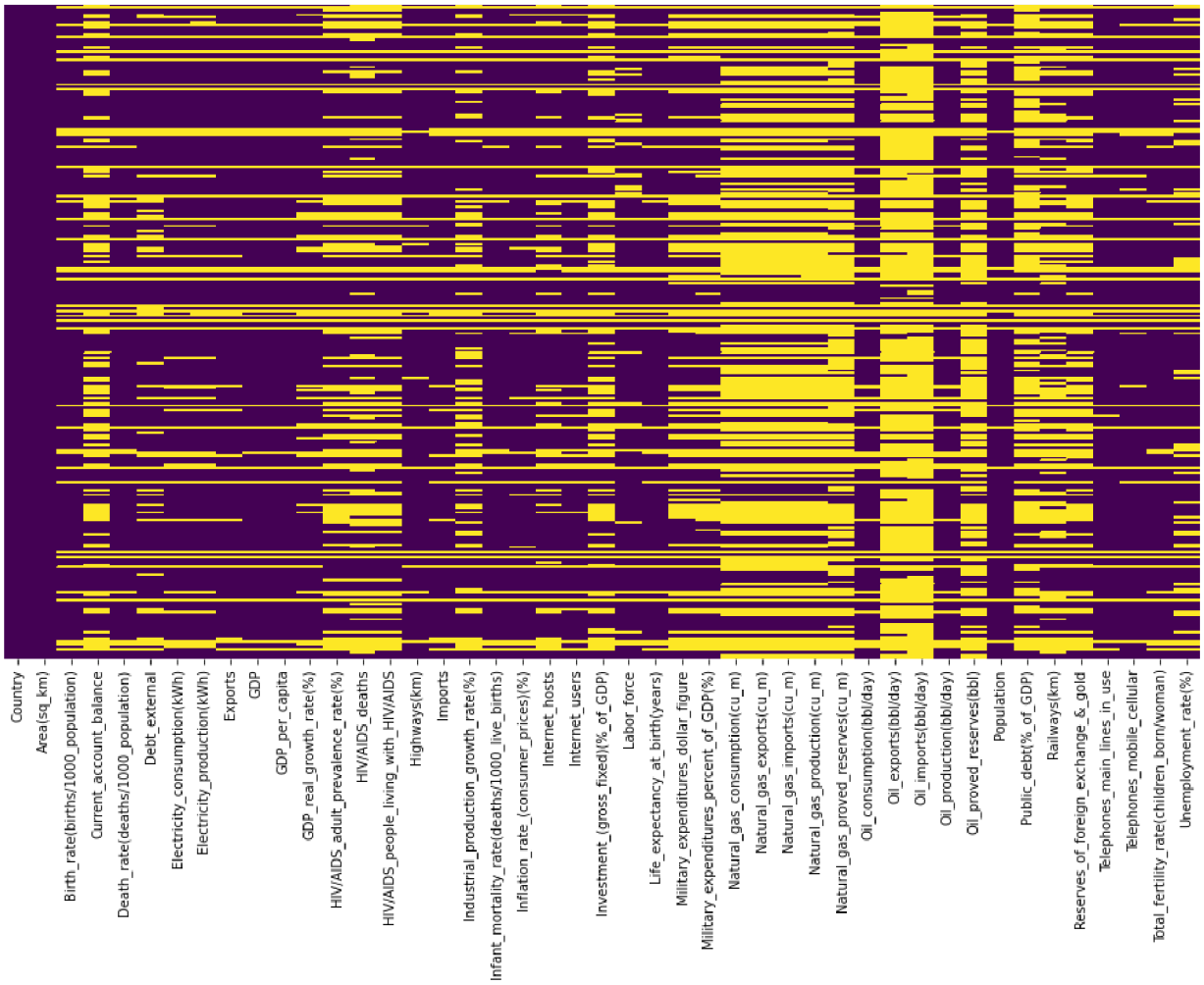
In [5]:
```
# load dataframe into database
df.to_sql("df", cnn, if_exists='replace')
print('...dataframe loaded into database')

```

```
...dataframe loaded into database
```

In [6]:
```
%load_ext sql
%sql sqlite:///df.db

```

In [7]:
```
# view dataset's null data, represented by yellow lines
plt.figure(figsize=(16,9))
sns.heatmap(df.isnull(), yticklabels=False, cbar=False, cmap='viridis')
```

Out[7]: <AxesSubplot:>



In [8]:
```
#%%sql
#select row_number() over ( order by Country) as RowNum, *from df where
```

In [9]:
```
# drop all rows where population is null
df.dropna(subset=['Population'],inplace=True)
```

In [10]:
```
# drop specific columns with no significant data, or missing too much d
df.drop('Natural_gas_consumption(cu_m)',axis=1,inplace=True)
df.drop('Natural_gas_exports(cu_m)',axis=1,inplace=True)
df.drop('Natural_gas_imports(cu_m)',axis=1,inplace=True)
df.drop('Natural_gas_production(cu_m)',axis=1,inplace=True)
df.drop('Natural_gas_proved_reserves(cu_m)',axis=1,inplace=True)
df.drop('Oil_exports(bbl/day)',axis=1,inplace=True)
df.drop('Oil_imports(bbl/day)',axis=1,inplace=True)
df.drop('Oil_proved_reserves(bbl)',axis=1,inplace=True)
df.drop('Public_debt(%_of_GDP)',axis=1,inplace=True)
df.drop('Current_account_balance',axis=1,inplace=True)
df.drop('Investment_(gross_fixed)(%_of_GDP)',axis=1,inplace=True)
df.drop('Railways(km)',axis=1,inplace=True)
df.drop('Reserves_of_foreign_exchange_&_gold',axis=1,inplace=True)
df.drop('Military_expenditures_dollar_figure',axis=1,inplace=True)
df.drop('Military_expenditures_percent_of_GDP(%)',axis=1,inplace=True)
df.drop('Industrial_production_growth_rate(%)',axis=1,inplace=True)
df.drop('HIV/AIDS_adult_prevalence_rate(%)',axis=1,inplace=True)
df.drop('HIV/AIDS_deaths',axis=1,inplace=True)
df.drop('HIV/AIDS_people_living_with_HIV/AIDS',axis=1,inplace=True)
```

In [11]:
```
# remaining column names with total null value rows
null_columns=df.columns[df.isnull().any()]
df[null_columns].isnull().sum()
df.head()
```

Out[11]:

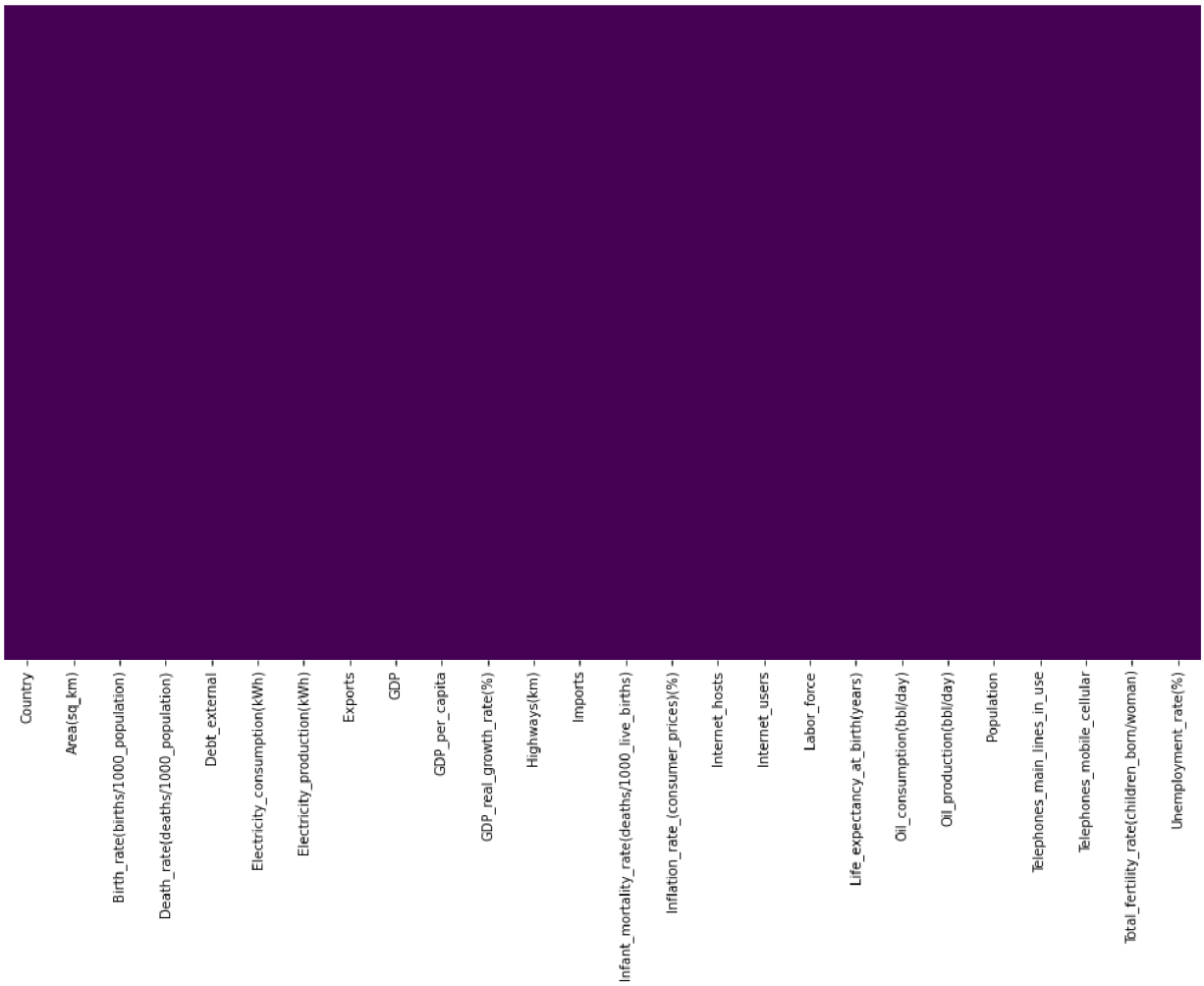
	Country	Area(sq_km)	Birth_rate(births/1000_population)	Death_rate(deaths/1000_population)	D
0	Afghanistan	647500	47.02	20.75	8.
2	Albania	28748	15.08	5.12	1.
3	Algeria	2381740	17.13	4.60	2.
4	American Samoa	199	23.13	3.33	
5	Andorra	468	9.00	6.07	

5 rows × 26 columns

In [12]:
```
set remaining null values to the mean of the column
Birth_rate(births/1000_population)'].fillna((df['Birth_rate(births/1000_p
Death_rate(deaths/1000_population)'].fillna((df['Death_rate(deaths/1000_p
Debt_external'].fillna((df['Debt_external'].mean()),inplace=True)
Electricity_consumption(kWh)'].fillna((df['Electricity_consumption(kWh)']
Electricity_production(kWh)'].fillna((df['Electricity_production(kWh)'].me
Exports'].fillna((df['Exports'].mean()),inplace=True)
GDP'].fillna((df['GDP'].mean()),inplace=True)
GDP_per_capita'].fillna((df['GDP_per_capita'].mean()),inplace=True)
GDP_real_growth_rate(%)'].fillna((df['GDP_real_growth_rate(%)'].mean()),i
Highways(km)'].fillna((df['Highways(km)'].mean()),inplace=True)
Imports'].fillna((df['Imports'].mean()),inplace=True)
Infant_mortality_rate(deaths/1000_live_births)'].fillna((df['Infant_morta
Inflation_rate_(consumer_prices)(%)'].fillna((df['Inflation_rate_(consume
Internet_hosts'].fillna((df['Internet_hosts'].mean()),inplace=True)
Internet_users'].fillna((df['Internet_users'].mean()),inplace=True)
Labor_force'].fillna((df['Labor_force'].mean()),inplace=True)
Life_expectancy_at_birth(years)'].fillna((df['Life_expectancy_at_birth(ye
Oil_consumption(bbl/day)'].fillna((df['Oil_consumption(bbl/day)'].mean())
Oil_production(bbl/day)'].fillna((df['Oil_production(bbl/day)'].mean()),i
Telephones_main_lines_in_use'].fillna((df['Telephones_main_lines_in_use']
Telephones_mobile_cellular'].fillna((df['Telephones_mobile_cellular'].mea
Total_fertility_rate(children_born/woman)'].fillna((df['Total_fertility_r
Unemployment_rate(%)'].fillna((df['Unemployment_rate(%)'].mean()),inplace
```

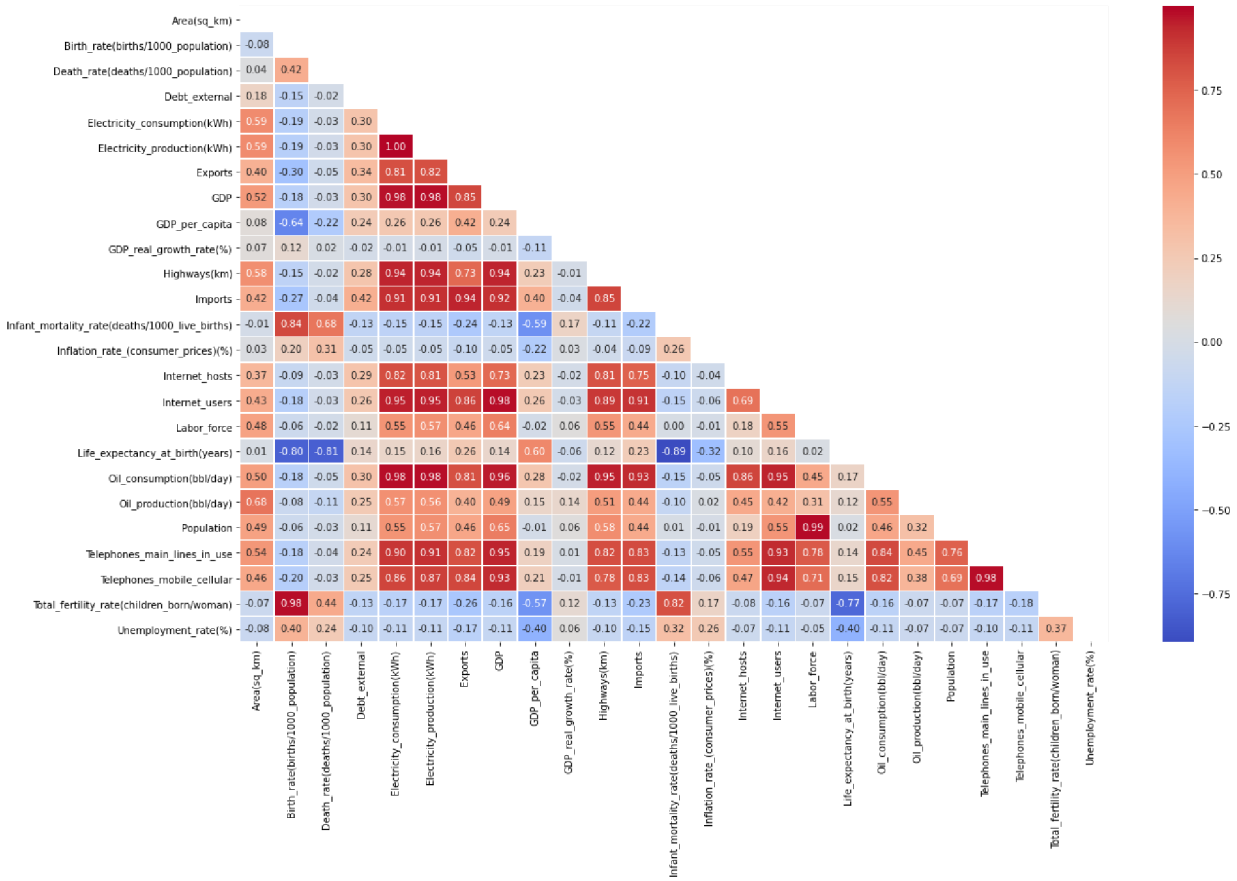
In [13]:
```
plt.figure(figsize = (16,9))
sns.heatmap(df.isnull(),yticklabels=False,cbar=False,cmap='viridis')
```

Out[13]: <AxesSubplot:>



In [14]:
```
# Pearson correlation matrix
pearsoncorr = df.corr(method='pearson')
plt.figure(figsize = (20,12))
sns.heatmap(pearsoncorr,
mask= np.triu(df.corr()),
xticklabels=pearsoncorr.columns, yticklabels=pearsoncorr.columns, cmap=
fmt=".2f",
annot=True, linewidth=0.5)
```

Out[14]: <AxesSubplot:>



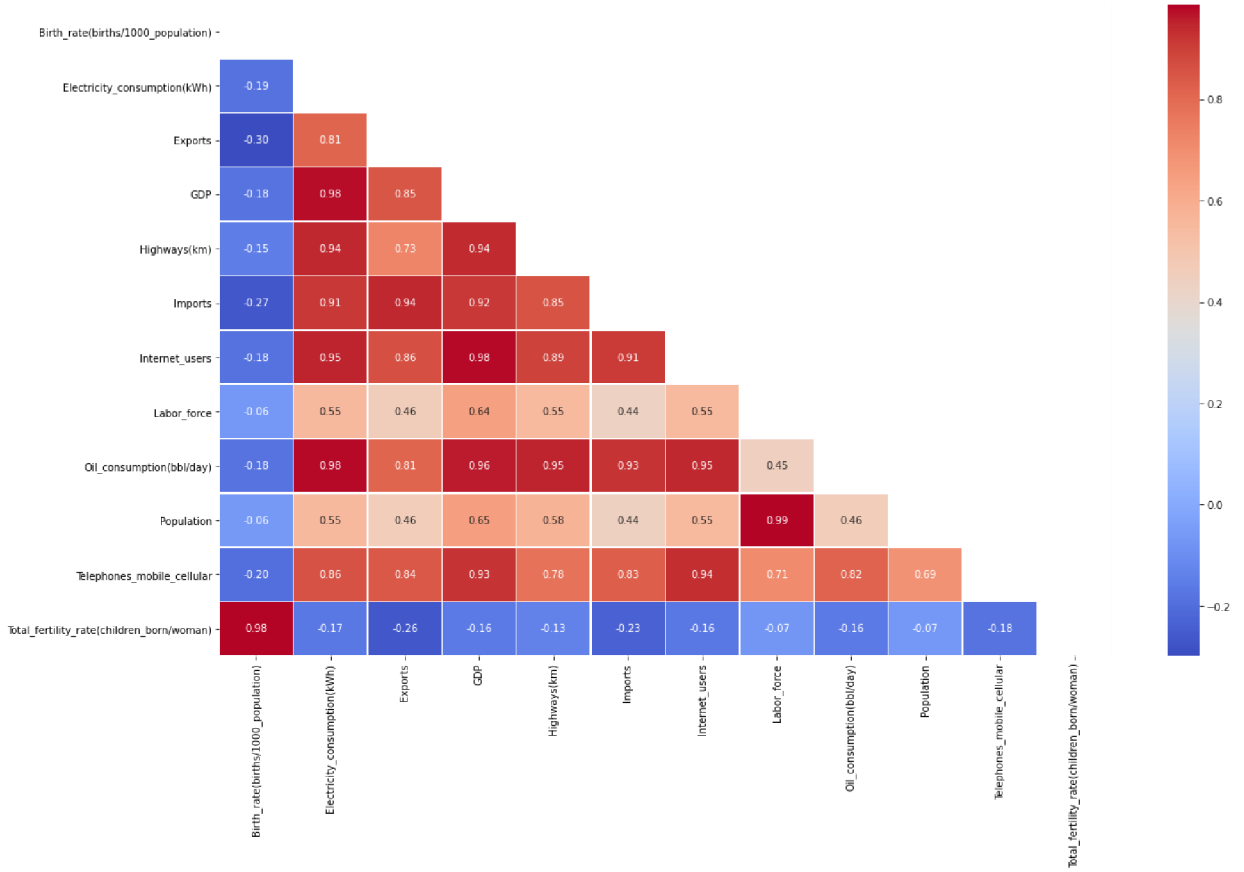
In [ ]:
```
1
```

In [15]:
```
# drop columns with no correlation value and/or that could cause multic
df.drop('Area(sq_km)', axis=1, inplace=True)
df.drop('Death_rate(deaths/1000_population)', axis=1, inplace=True)
df.drop('Debt_external', axis=1, inplace=True)
df.drop('GDP_per_capita', axis=1, inplace=True)
df.drop('GDP_real_growth_rate(%)', axis=1, inplace=True)
df.drop('Infant_mortality_rate(deaths/1000_live_births)', axis=1, inpla
df.drop('Inflation_rate_(consumer_prices)(%)', axis=1, inplace=True)
df.drop('Internet_hosts', axis=1, inplace=True)
df.drop('Life_expectancy_at_birth(years)', axis=1, inplace=True)
df.drop('Oil_production(bbl/day)', axis=1, inplace=True)
df.drop('Unemployment_rate(%)', axis=1, inplace=True)
```

In [16]:
```
# potential multicollinearity issue
df.drop('Electricity_production(kWh)', axis=1, inplace=True)
df.drop('Telephones_main_lines_in_use', axis=1, inplace=True)
```

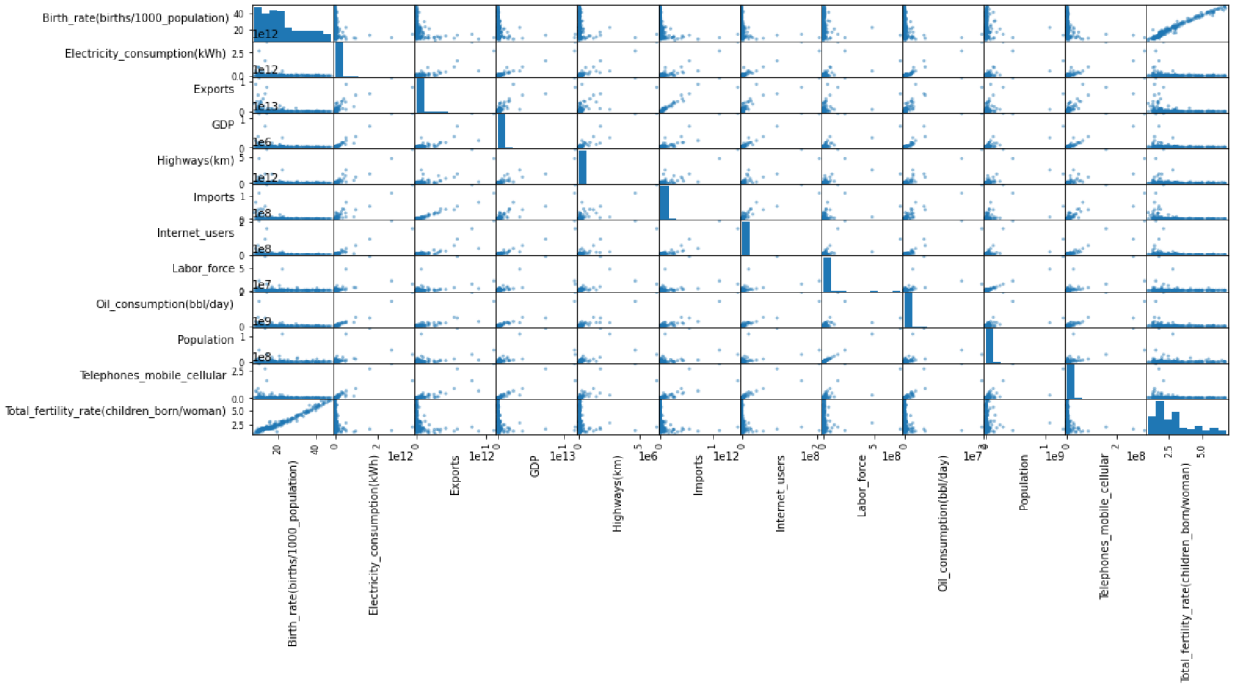
In [17]:
```
# 2nd Pearson correlation matrix
pearsoncorr2 = df.corr(method='pearson')
plt.figure(figsize = (20,12))
sns.heatmap(pearsoncorr2,
mask= np.triu(df.corr()),
xticklabels=pearsoncorr2.columns, yticklabels=pearsoncorr2.columns, cma
fmt=".2f",
annot=True, linewidth=0.5)
```

Out[17]: <AxesSubplot:>



In [18]:
```
import statsmodels.api as sm
import statsmodels.stats.outliers_influence as inf

#
plt.figure(figsize = (16,9))
axes = pd.plotting.scatter_matrix(df, figsize=(16,9))
for ax in axes.flatten():
    ax.xaxis.label.set_rotation(90)
    ax.yaxis.label.set_rotation(0)
    ax.yaxis.label.set_ha('right')

plt.tight_layout()
plt.gcf().subplots_adjust(wspace=0, hspace=0)
plt.show()
```

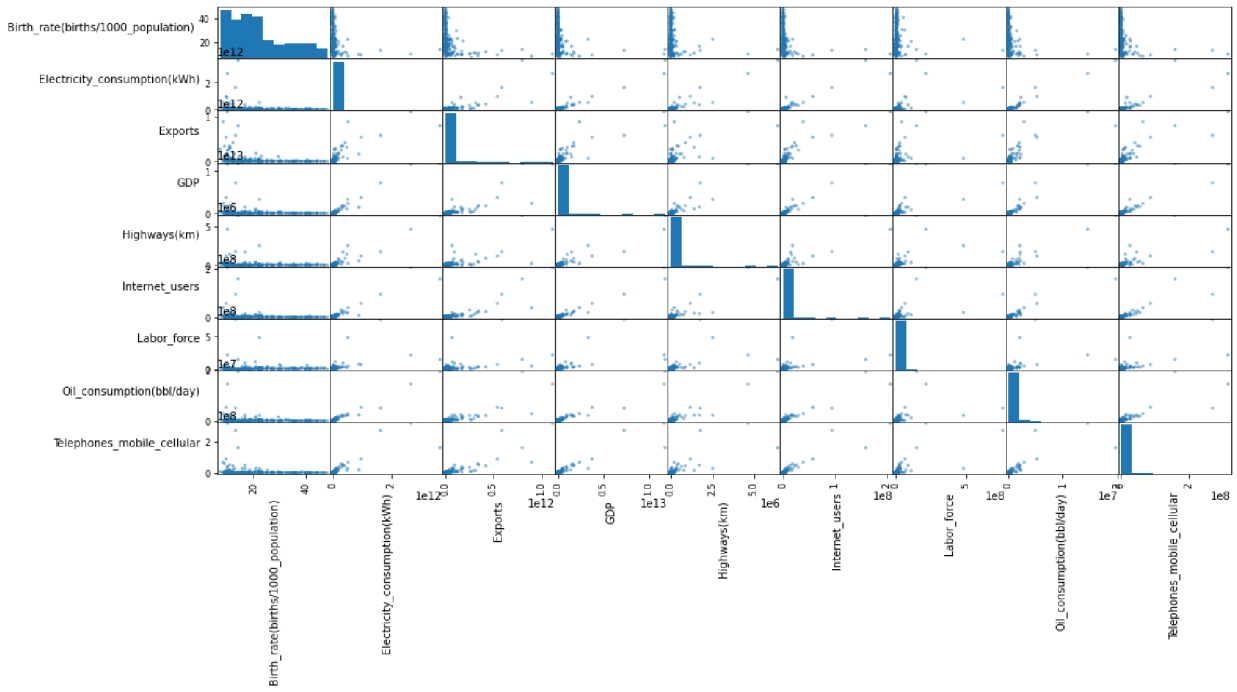
```
<Figure size 1152x648 with 0 Axes>
```



In [19]:
```
df.drop('Total_fertility_rate(children_born/woman)', axis=1, inplace=Tr
df.drop('Population', axis=1, inplace=True)
df.drop('Imports', axis=1, inplace=True)
```

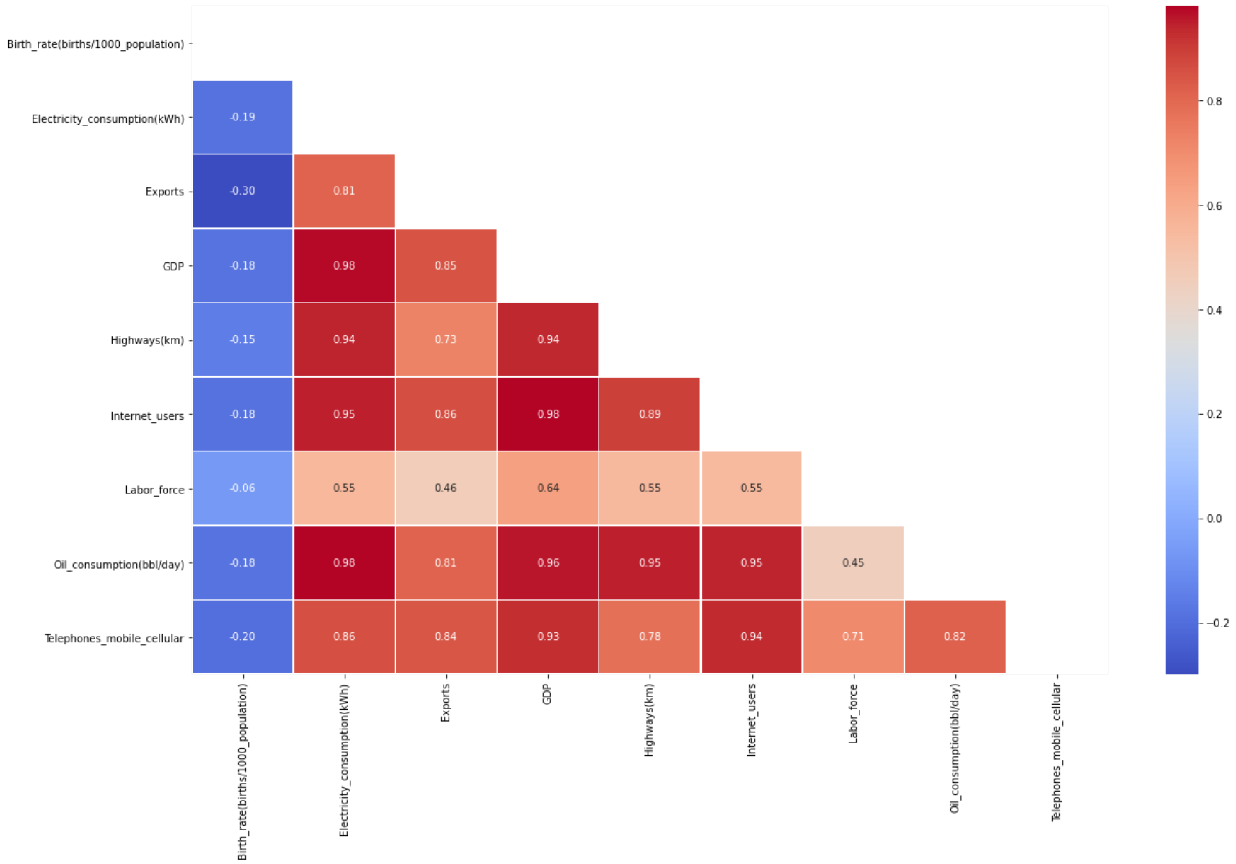
In [20]:
```
plt.figure(figsize = (16,9))
axes = pd.plotting.scatter_matrix(df, figsize=(16,9))
for ax in axes.flatten():
    ax.xaxis.label.set_rotation(90)
    ax.yaxis.label.set_rotation(0)
    ax.yaxis.label.set_ha('right')

plt.tight_layout()
plt.gcf().subplots_adjust(wspace=0, hspace=0)
plt.show()
```

```
<Figure size 1152x648 with 0 Axes>
```



In [21]:
```
pearsoncorr3 = df.corr(method='pearson')
plt.figure(figsize = (20,12))
sns.heatmap(pearsoncorr3,
mask= np.triu(df.corr()),
xticklabels=pearsoncorr3.columns, yticklabels=pearsoncorr3.columns, cma
fmt=".2f",
annot=True, linewidth=0.5)
```

Out[21]: <AxesSubplot:>



In [22]:
```
#Splitting the data, leaving 25% for testing
from sklearn.model_selection import train_test_split
import random
```

In [23]:
```
df_train, df_test = train_test_split(df, test_size = 0.25, random_state
```

In [24]:
```
print(" Original = ", len(df), '\n',
"Test Size = ", len(df_test), '\n',
"Train Size = ", len(df_train))
```

```
Original =  238
Test Size =  60
Train Size =  178
```

In [25]:
```
list(df_train)
```

Out[25]:
```
['Country',
 'Birth_rate(births/1000_population)',
 'Electricity_consumption(kWh)',
 'Exports',
 'GDP',
 'Highways(km)',
 'Internet_users',
 'Labor_force',
 'Oil_consumption(bbl/day)',
 'Telephones_mobile_cellular']
```

In [32]:
```
X = pd.DataFrame(df_train[['Birth_rate(births/1000_population)',
                           'Electricity_consumption(kWh)',
                           'Exports',
                           'Highways(km)',
                           'Internet_users',
                           'Labor_force',
                           'Oil_consumption(bbl/day)',
                           'Telephones_mobile_cellular']])
y = pd.DataFrame(df_train[['GDP']])
```

In [33]:
```
X = sm.add_constant(X)
X.head()
```

Out[33]:

	const	Birth_rate(births/1000_population)	Electricity_consumption(kWh)	Exports	Highways(
17	1.0	17.87	1.596000e+09	6.360000e+08	26
33	1.0	16.83	3.519000e+11	9.500000e+10	17249
146	1.0	12.00	7.216000e+09	1.629000e+09	86
47	1.0	45.98	8.940000e+07	3.650000e+08	334
53	1.0	20.82	4.114000e+10	1.550000e+10	1129

In [34]:
```
model_1 = sm.OLS(y, X).fit()
```

In [35]:
```
model_1.summary2()
```

Out[35]:

Model:	OLS	Adj. R-squared:	0.995
Dependent Variable:	GDP	AIC:	9439.4275
Date:	2021-08-05 02:01	BIC:	9468.0635
No. Observations:	178	Log-Likelihood:	-4710.7
Df Model:	8	F-statistic:	4329.
Df Residuals:	169	Prob (F-statistic):	3.28e-191
R-squared:	0.995	Scale:	5.9840e+21

	Coef.	Std.Err.	t	P>|t|	
const	-49170293910.6073	15137352218.1721	-3.2483	0.0014	-790529476
Birth_rate(births/1000_population)	1334561993.4576	602170074.3273	2.2163	0.0280	1458177
Electricity_consumption(kWh)	0.3809	0.2114	1.8021	0.0733	-
Exports	0.3448	0.1303	2.6457	0.0089	
Highways(km)	203369.8358	45980.3133	4.4230	0.0000	1126
Internet_users	17170.1394	2627.0329	6.5359	0.0000	119
Labor_force	576.2012	331.3590	1.7389	0.0839	-7
Oil_consumption(bbl/day)	96493.3385	35677.8362	2.7046	0.0075	260
Telephones_mobile_cellular	13529.3970	1498.3084	9.0298	0.0000	105

Omnibus:	49.258	Durbin-Watson:	2.164
Prob(Omnibus):	0.000	Jarque-Bera (JB):	454.002
Skew:	-0.666	Prob(JB):	0.000
Kurtosis:	10.710	Condition No.:	742037871474

In [45]:
```
X2 = pd.DataFrame(df_train[['Highways(km)',
                            'Internet_users',
                            'Oil_consumption(bbl/day)',
                            'Telephones_mobile_cellular']])
```

In [46]:
```
X2 = sm.add_constant(X2)
```

In [47]:
```
model_2 = sm.OLS(y, X2).fit()
```

In [48]:
```
1 model_2.summary2()
```

Out[48]:

Model:	OLS	Adj. R-squared:	0.994
Dependent Variable:	GDP	AIC:	9451.2238
Date:	2021-08-05 02:07	BIC:	9467.1328
No. Observations:	178	Log-Likelihood:	-4720.6
Df Model:	4	F-statistic:	7926.
Df Residuals:	173	Prob (F-statistic):	9.54e-195
R-squared:	0.995	Scale:	6.5333e+21

	Coef.	Std.Err.	t	P>|t|	[0.025
const	-12354676094.6805	6644084929.6895	-1.8595	0.0647	-25468580488.7164
Highways(km)	220771.9588	45887.5118	4.8112	0.0000	130200.5032
Internet_users	14732.7385	2348.7209	6.2727	0.0000	10096.9006
Oil_consumption(bbl/day)	141202.9873	27979.4444	5.0467	0.0000	85977.9620
Telephones_mobile_cellular	17775.3663	683.8909	25.9915	0.0000	16425.5220

Omnibus:	36.809	Durbin-Watson:	2.204
Prob(Omnibus):	0.000	Jarque-Bera (JB):	425.640
Skew:	-0.027	Prob(JB):	0.000
Kurtosis:	10.575	Condition No.:	41038836

In [ ]:
```
1
```

In [43]:
```
1 #Running test data through models
2 X_test = pd.DataFrame(df_test[['Highways(km)',
3                                'Internet_users',
4                                'Oil_consumption(bbl/day)',
5                                'Telephones_mobile_cellular']])
6 y_test = pd.DataFrame(df_test[['GDP']])
```

In [44]:
```
1 X_test = sm.add_constant(X_test)
```

In [50]:
```
model_3_test = sm.OLS(y_test, X_test).fit()
model_3_test.summary2()
```

Out[50]:

Model:	OLS	Adj. R-squared:	0.992
Dependent Variable:	GDP	AIC:	3254.5485
Date:	2021-08-05 02:15	BIC:	3265.0202
No. Observations:	60	Log-Likelihood:	-1622.3
Df Model:	4	F-statistic:	1907.
Df Residuals:	55	Prob (F-statistic):	2.90e-58
R-squared:	0.993	Scale:	1.9505e+22

	Coef.	Std.Err.	t	P>|t|	[0.02
const	-24679007168.7042	19646063591.2254	-1.2562	0.2144	-64050598391.810
Highways(km)	824787.5890	66087.0220	12.4803	0.0000	692346.237
Internet_users	10929.9778	7113.0340	1.5366	0.1301	-3324.861
Oil_consumption(bbl/day)	114784.8917	53665.3984	2.1389	0.0369	7237.030
Telephones_mobile_cellular	16356.2837	3259.0887	5.0187	0.0000	9824.923

Omnibus:	17.280	Durbin-Watson:	1.782
Prob(Omnibus):	0.000	Jarque-Bera (JB):	77.480
Skew:	-0.395	Prob(JB):	0.000
Kurtosis:	8.511	Condition No.:	34539584