Data Management and Visualization

Developing a Research Question and Creating Your Personal Code Book

STEP 1: Choose a data set that you would like to work with.

I am choosing GapMinder dataset.

STEP 2. Identify a specific topic of interest

I am exploring is there a relationship on Polity scores with life expectancy.

STEP 3. Prepare a codebook of your own (i.e., print individual pages or copy screen and paste into a new document) from the larger codebook that includes the questions/items/variables that measure your selected topics.)

Data Dictionary

Field	Description
country	Unique Identifier
incomeperperson	2010 Gross Domestic Product per capita in constant 2000 US$
alcconsumption	2008 alcohol consumption per adult (age 15+), litres
armedforcesrate	Armed forces personnel (% of total labor force)
breastcancerper100th	2002 breast cancer new cases per 100,000 female
co2emissions	2006 cumulative CO2 emission (metric tons)
femaleemployrate	2007 female employees age 15+ (% of population)
hivrate	2009 estimated HIV Prevalence % - (Ages 15-49)
internetuserate	2010 Internet users (per 100 people)
lifeexpectancy	2011 life expectancy at birth (years)
oilperperson	2010 oil Consumption per capita (tonnes per year and person)
polityscore	2009 Democracy score (Polity)
relectricperperson	2008 residential electricity consumption, per person (kWh)
suicideper100th	2005 Suicide, age adjusted, per 100 000
employrate	2007 total employees age 15+ (% of population)
urbanrate	2008 urban population (% of total)

STEP 4. Identify a second topic that you would like to explore in terms of its association with your original topic

The second one is has employment rate influence urban rates.

STEP 5. Add questions/items/variables documenting this second topic to your personal codebook

STEP 6. Perform a literature review to see what research has been previously done on this topic.

Ref 1: Health advocacy with Gapminder animated statistics

Ref 2: Formalizing students' informal statistical reasoning on real data: Using Gapminder to follow the cycle of inquiry and visual analyses

Ref 3: USE OF TED.COM and GAPMINDER.ORG IN TEACHING APPLICATIONS OF MATHEMATICS AND STATISTICS

STEP 7. Based on your literature review, develop a hypothesis about what you believe the association might be between these topics. Be sure to integrate the specific variables you selected into the hypothesis.

Hypothesis suggested: Has suicide rate influenced by HIV rate on victims?

Running Your First Program

STEP 1: Run your first program. This program will be used throughout the remainder of the course and become the basis of your data analysis going forward.

Import Libraries

In [1]:
```
import numpy as np
from numpy import count_nonzero
from numpy import median
from numpy import mean
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import random

import statsmodels.api as sm
import statsmodels.formula.api as smf
from statsmodels.formula.api import ols

import datetime
from datetime import datetime, timedelta

import scipy.stats
from collections import Counter


import sklearn
from sklearn.preprocessing import StandardScaler, MinMaxScaler, LabelEncoder, OneHotEncoder
from sklearn.linear_model import LinearRegression, LogisticRegression, ElasticNet, Lasso, Ridge
from sklearn.model_selection import cross_val_score, train_test_split
from sklearn.metrics import accuracy_score, auc, classification_report, confusion_matrix, f1_score
from sklearn.metrics import plot_confusion_matrix, plot_roc_curve

%matplotlib inline
#sets the default autosave frequency in seconds
%autosave 60
sns.set_style('dark')
sns.set(font_scale=1.2)

plt.rc('axes', titlesize=9)
plt.rc('axes', labelsize=14)
plt.rc('xtick', labelsize=12)
plt.rc('ytick', labelsize=12)

import warnings
warnings.filterwarnings('ignore')

# Use Feature-Engine library
import feature_engine
from feature_engine import imputation as mdi
#from feature_engine.outlier_removers import Winsorizer
#from feature_engine import categorical_encoders as ce
from feature_engine.discretisation import EqualWidthDiscretiser, EqualFrequencyDiscretiser, ArbitraryDiscretise
#from feature_engine.encoding import OrdinalEncoder

pd.set_option('display.max_columns',None)
#pd.set_option('display.max_rows',None)
pd.set_option('display.width', 1000)
pd.set_option('display.float_format','{:.2f}'.format)

random.seed(0)
np.random.seed(0)
np.set_printoptions(suppress=True)
```

```
Autosaving every 60 seconds
```

Exploratory Data Analysis

In [2]:
```
df = pd.read_csv("gapminder.csv")
```

In [3]:
```
df
```

Out[3]:

	country	incomeperperson	alcconsumption	armedforcesrate	breastcancerper100th	co2emissions	femaleemployrate	hivrate	int
0	Afghanistan		.03	.5696534	26.8	75944000	25.6000003814697		3.654
1	Albania	1914.99655094922	7.29	1.0247361	57.4	223747333.333333	42.0999984741211		44.98
2	Algeria	2231.99333515006	.69	2.306817	23.5	2932108666.66667	31.7000007629394	.1	12.50
3	Andorra	21943.3398976022	10.17						
4	Angola	1381.00426770244	5.57	1.4613288	23.1	248358000	69.4000015258789	2	9.999
...	...	...	...	...	...	...	...	...	...
208	Vietnam	722.807558834445	3.91	1.0853671	16.2	1425435000	67.5999984741211	.4	27.85
209	West Bank and Gaza			5.9360854		14241333.3333333	11.3000001907349		36.42
210	Yemen, Rep.	610.3573673206	.2	2.3162346	35.1	234864666.666667	20.2999992370605		12.34
211	Zambia	432.226336974583	3.56	.3413352	13	132025666.666667	53.5	13.5	10.1
212	Zimbabwe	320.771889948584	4.96	1.0327854	19	590219666.666666	58.0999984741211	14.3	11.50

213 rows × 16 columns

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 213 entries, 0 to 212
Data columns (total 16 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   country               213 non-null    object
 1   incomeperperson       213 non-null    object
 2   alcconsumption        213 non-null    object
 3   armedforcesrate       213 non-null    object
 4   breastcancerper100th  213 non-null    object
 5   co2emissions          213 non-null    object
 6   femaleemployrate      213 non-null    object
 7   hivrate               213 non-null    object
 8   internetuserate       213 non-null    object
 9   lifeexpectancy        213 non-null    object
 10  oilperperson          213 non-null    object
 11  polityscore           213 non-null    object
 12  relectricperperson    213 non-null    object
 13  suicideper100th       213 non-null    object
 14  employrate            213 non-null    object
 15  urbanrate             213 non-null    object
dtypes: object(16)
memory usage: 26.8+ KB
```

STEP 2: Run frequency distributions for your chosen variables and select columns, and possibly rows.

In [5]:
```
df.columns
```

Out[5]:
```
Index(['country', 'incomeperperson', 'alcconsumption', 'armedforcesrate', 'breastcancerper100th', 'co2emission
s', 'femaleemployrate', 'hivrate', 'internetuserate', 'lifeexpectancy', 'oilperperson', 'polityscore', 'relectr
icperperson', 'suicideper100th', 'employrate', 'urbanrate'], dtype='object')
```

In [6]:
```
df2 = df[['lifeexpectancy','polityscore','employrate', 'urbanrate','suicideper100th','hivrate']]
```

In [7]:
```
df2
```

Out[7]:

	lifeexpectancy	polityscore	employrate	urbanrate	suicideper100th	hivrate
0	48.673	0	55.7000007629394	24.04	6.68438529968262	
1	76.918	9	51.4000015258789	46.72	7.69932985305786	
2	73.131	2	50.5	65.22	4.8487696647644	.1
3				88.92	5.36217880249023	
4	51.093	-2	75.6999969482422	56.7	14.5546770095825	2
...	...	...	...	...	...	...
208	75.181	-7	71	27.84	11.6533222198486	.4
209	72.832		32	71.9		
210	65.493	-2	39	30.64	6.26578903198242	
211	49.025	7	61	35.42	12.0190362930298	13.5
212	51.384	1	66.8000030517578	37.34	13.9052667617798	14.3

213 rows × 6 columns

Type Change

In [8]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 213 entries, 0 to 212
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   lifeexpectancy   213 non-null    object
 1   polityscore      213 non-null    object
 2   employrate       213 non-null    object
 3   urbanrate        213 non-null    object
 4   suicideper100th  213 non-null    object
 5   hivrate          213 non-null    object
dtypes: object(6)
memory usage: 10.1+ KB
```

In [9]:
```
df2 = df2.replace(r'^\s*$', np.nan, regex=True)
```

In [10]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 213 entries, 0 to 212
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   lifeexpectancy   191 non-null    object
 1   polityscore      161 non-null    object
 2   employrate       178 non-null    object
 3   urbanrate        203 non-null    object
 4   suicideper100th  191 non-null    object
 5   hivrate          147 non-null    object
dtypes: object(6)
memory usage: 10.1+ KB
```

In [11]:
```
df2["lifeexpectancy"] = df2["lifeexpectancy"].astype("float")
```

In [12]:
```
df2["polityscore"] = df2["polityscore"].astype("float")
```

In [13]:
```
df2["employrate"] = df2["employrate"].astype("float")
```

In [14]:
```
df2["urbanrate"] = df2["urbanrate"].astype("float")
```

In [15]:
```
df2["suicideper100th"] = df2["suicideper100th"].astype("float")
```

In [16]:
```
df2["hivrate"] = df2["hivrate"].astype("float")
```

In [17]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 213 entries, 0 to 212
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   lifeexpectancy   191 non-null    float64
 1   polityscore      161 non-null    float64
 2   employrate       178 non-null    float64
 3   urbanrate        203 non-null    float64
 4   suicideper100th  191 non-null    float64
 5   hivrate          147 non-null    float64
dtypes: float64(6)
memory usage: 10.1 KB
```

In [18]:
```
df2
```

Out[18]:

	lifeexpectancy	polityscore	employrate	urbanrate	suicideper100th	hivrate
0	48.67	0.00	55.70	24.04	6.68	NaN
1	76.92	9.00	51.40	46.72	7.70	NaN
2	73.13	2.00	50.50	65.22	4.85	0.10
3	NaN	NaN	NaN	88.92	5.36	NaN
4	51.09	-2.00	75.70	56.70	14.55	2.00
...	...	...	...	...	...	...
208	75.18	-7.00	71.00	27.84	11.65	0.40
209	72.83	NaN	32.00	71.90	NaN	NaN
210	65.49	-2.00	39.00	30.64	6.27	NaN
211	49.02	7.00	61.00	35.42	12.02	13.50
212	51.38	1.00	66.80	37.34	13.91	14.30

213 rows × 6 columns

In [19]:
```
#df2.to_csv("gapminder_research.csv", index=False)
```

Groupby Function

In [20]:
```
df2.groupby(["polityscore"]).count()
```

Out[20]:

polityscore	lifeexpectancy	employrate	urbanrate	suicideper100th	hivrate
-10.00	2	2	2	2	1
-9.00	4	4	4	4	2
-8.00	2	2	2	2	1
-7.00	12	12	12	12	8
-6.00	3	3	3	3	3
-5.00	2	2	2	2	2
-4.00	6	6	6	6	6
-3.00	6	6	6	6	4
-2.00	5	5	5	5	4
-1.00	4	4	4	4	4
0.00	6	6	6	6	4
1.00	3	3	3	3	2
2.00	3	2	3	3	3
3.00	2	2	2	2	2
4.00	4	4	4	4	4
5.00	7	7	7	7	6
6.00	10	10	10	10	10
7.00	13	13	13	13	12
8.00	19	18	19	19	18
9.00	15	14	15	14	12
10.00	32	33	32	32	31

In [21]:
```
df2.describe()
```

Out[21]:

	lifeexpectancy	polityscore	employrate	urbanrate	suicideper100th	hivrate
count	191.00	161.00	178.00	203.00	191.00	147.00
mean	69.75	3.69	58.64	56.77	9.64	1.94
std	9.71	6.31	10.52	23.84	6.30	4.38
min	47.79	-10.00	32.00	10.40	0.20	0.06
25%	64.45	-2.00	51.23	36.83	4.99	0.10
50%	73.13	6.00	58.70	57.94	8.26	0.40
75%	76.59	9.00	64.98	74.21	12.33	1.30
max	83.39	10.00	83.20	100.00	35.75	25.90

Making Data Management Decisions

STEP 1: Make and implement data management decisions for the variables you selected

In [22]:
```
df2 = pd.read_csv("gapminder_research.csv")
df2.head()
```

Out[22]:

	lifeexpectancy	polityscore	employrate	urbanrate	suicideper100th	hivrate
0	48.67	0.00	55.70	24.04	6.68	NaN
1	76.92	9.00	51.40	46.72	7.70	NaN
2	73.13	2.00	50.50	65.22	4.85	0.10
3	NaN	NaN	NaN	88.92	5.36	NaN
4	51.09	-2.00	75.70	56.70	14.55	2.00

Treat Missing Values

In [23]:
```
df2.isnull().sum()
```

Out[23]:
```
lifeexpectancy     22
polityscore        52
employrate         35
urbanrate          10
suicideper100th    22
hivrate            66
dtype: int64
```

In [24]:
```
df2.describe()
```

Out[24]:

	lifeexpectancy	polityscore	employrate	urbanrate	suicideper100th	hivrate
count	191.00	161.00	178.00	203.00	191.00	147.00
mean	69.75	3.69	58.64	56.77	9.64	1.94
std	9.71	6.31	10.52	23.84	6.30	4.38
min	47.79	-10.00	32.00	10.40	0.20	0.06
25%	64.45	-2.00	51.23	36.83	4.99	0.10
50%	73.13	6.00	58.70	57.94	8.26	0.40
75%	76.59	9.00	64.98	74.21	12.33	1.30
max	83.39	10.00	83.20	100.00	35.75	25.90

In [25]:
```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 213 entries, 0 to 212
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   lifeexpectancy   191 non-null    float64
 1   polityscore      161 non-null    float64
 2   employrate       178 non-null    float64
 3   urbanrate        203 non-null    float64
 4   suicideper100th  191 non-null    float64
 5   hivrate          147 non-null    float64
dtypes: float64(6)
memory usage: 10.1 KB
```

In [26]:
```
imputer = mdi.MeanMedianImputer(imputation_method='median',variables=None)
```

In [27]:
```
imputer.fit(df2)
```

Out[27]:
```
MeanMedianImputer()
```

In [28]:
```
imputer.imputer_dict_
```

Out[28]:
```
{'lifeexpectancy': 73.131,
 'polityscore': 6.0,
 'employrate': 58.69999885559085,
 'urbanrate': 57.94,
 'suicideper100th': 8.2628927230835,
 'hivrate': 0.4}
```

In [29]:
```
df3 = imputer.transform(df2)
```

In [30]:
```
df3
```

Out[30]:

	lifeexpectancy	polityscore	employrate	urbanrate	suicideper100th	hivrate
0	48.67	0.00	55.70	24.04	6.68	0.40
1	76.92	9.00	51.40	46.72	7.70	0.40
2	73.13	2.00	50.50	65.22	4.85	0.10
3	73.13	6.00	58.70	88.92	5.36	0.40
4	51.09	-2.00	75.70	56.70	14.55	2.00
...	...	...	...	...	...	...
208	75.18	-7.00	71.00	27.84	11.65	0.40
209	72.83	6.00	32.00	71.90	8.26	0.40
210	65.49	-2.00	39.00	30.64	6.27	0.40
211	49.02	7.00	61.00	35.42	12.02	13.50
212	51.38	1.00	66.80	37.34	13.91	14.30

213 rows × 6 columns

In [31]:
```
df3.isnull().sum()
```

Out[31]:
```
lifeexpectancy     0
polityscore        0
employrate         0
urbanrate          0
suicideper100th    0
hivrate            0
dtype: int64
```

In [32]:
```
#df3.to_csv("gapminderfinal.csv", index=False)
```

Equal Width Discretization

In [33]:
```
df3["democscorecat"] = df3["polityscore"] #Make a copy
```

In [34]:
```
disc = EqualWidthDiscretiser(bins=4, variables=['democscorecat'], return_object=True)
```

In [35]:
```
disc
```

Out[35]:
```
EqualWidthDiscretiser(bins=4, return_object=True, variables=['democscorecat'])
```

In [36]:
```
disc.fit(df3)
```

Out[36]:
```
EqualWidthDiscretiser(bins=4, return_object=True, variables=['democscorecat'])
```

In [37]:
```
disc.binner_dict_
```

Out[37]:
```
{'democscorecat': [-inf, -5.0, 0.0, 5.0, inf]}
```

In [38]:
```
df4 = disc.fit_transform(df3)
df4.head()
```

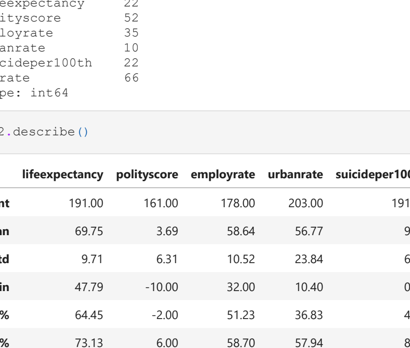
Out[38]:

	lifeexpectancy	polityscore	employrate	urbanrate	suicideper100th	hivrate	democscorecat
0	48.67	0.00	55.70	24.04	6.68	0.40	1
1	76.92	9.00	51.40	46.72	7.70	0.40	3
2	73.13	2.00	50.50	65.22	4.85	0.10	2
3	73.13	6.00	58.70	88.92	5.36	0.40	3
4	51.09	-2.00	75.70	56.70	14.55	2.00	1

In [39]:
```
df4["democscorecat"].value_counts()
```

Out[39]:
```
3    142
1     27
0     25
2     19
Name: democscorecat, dtype: int64
```

In [40]:
```
df4["democscorecat"].value_counts().plot.bar()
plt.show()
```



In [41]:
```
#df4.to_csv("gapminderfinal.csv", index=False)
```

STEP 2: Run frequency distributions for your chosen variables and select columns, and possibly rows.

In short, I have encoded the polityscore variable into 4 parts and settled all missing data.

Creating graphs for your data

In [42]:
```
df4 = pd.read_csv("gapminderfinal.csv")
df4
```

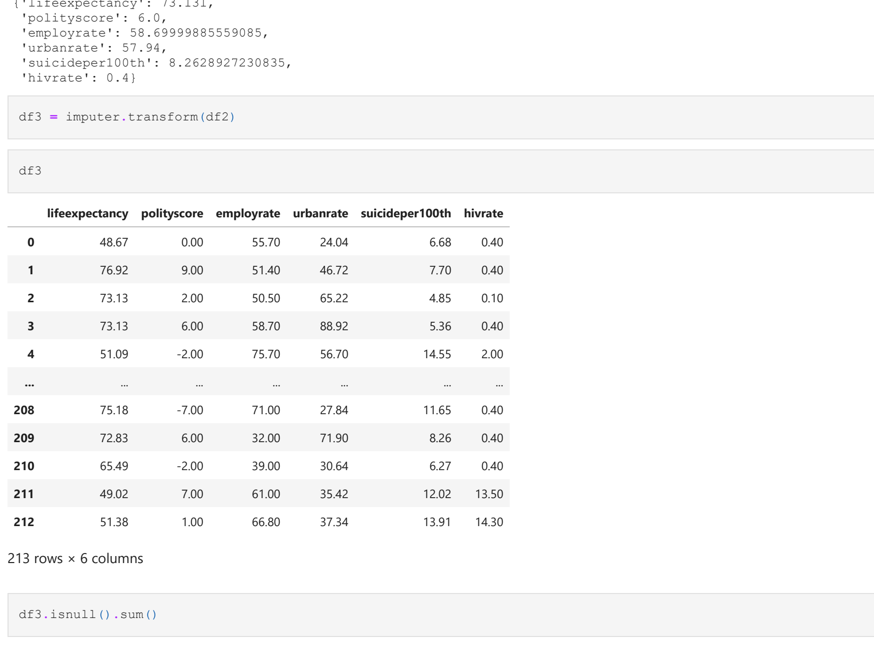
Out[42]:

	lifeexpectancy	polityscore	employrate	urbanrate	suicideper100th	hivrate	democscorecat
0	48.67	0.00	55.70	24.04	6.68	0.40	1
1	76.92	9.00	51.40	46.72	7.70	0.40	3
2	73.13	2.00	50.50	65.22	4.85	0.10	2
3	73.13	6.00	58.70	88.92	5.36	0.40	3
4	51.09	-2.00	75.70	56.70	14.55	2.00	1
...	...	...	...	...	...	...	...
208	75.18	-7.00	71.00	27.84	11.65	0.40	0
209	72.83	6.00	32.00	71.90	8.26	0.40	3
210	65.49	-2.00	39.00	30.64	6.27	0.40	1
211	49.02	7.00	61.00	35.42	12.02	13.50	3
212	51.38	1.00	66.80	37.34	13.91	14.30	2

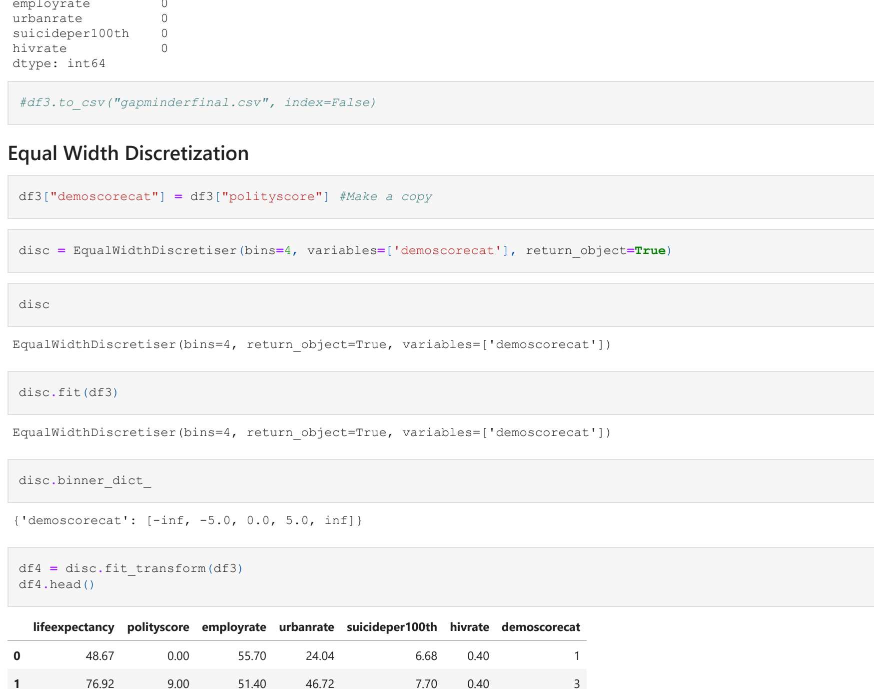
213 rows × 7 columns

STEP 1: Create graphs of your variables one at a time (univariate graphs)

In [43]:
```
df4.hist(bins=50, figsize=(20,10))
plt.suptitle('Univariate Feature Distribution', x=0.5, y=1.02, ha='center', fontsize=20)
plt.tight_layout()
plt.show()
```



In [44]:
```
df4.boxplot(figsize=(20,10))
plt.suptitle('BoxPlots Feature Distribution', x=0.5, y=1.02, ha='center', fontsize=20)
plt.tight_layout()
plt.show()
```



STEP 2: Create a graph showing the association between your explanatory and response variables (bivariate graph)

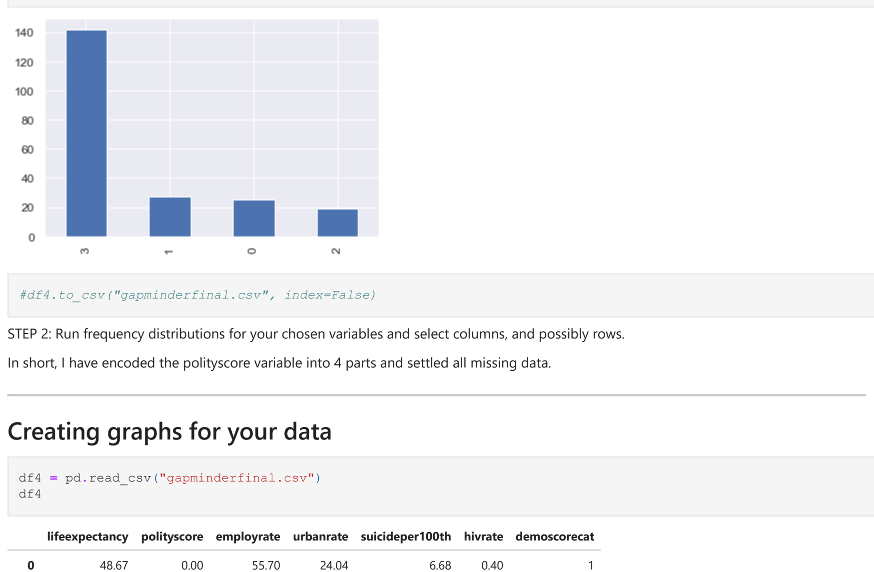
Relationship on Polity scores with life expectancy.

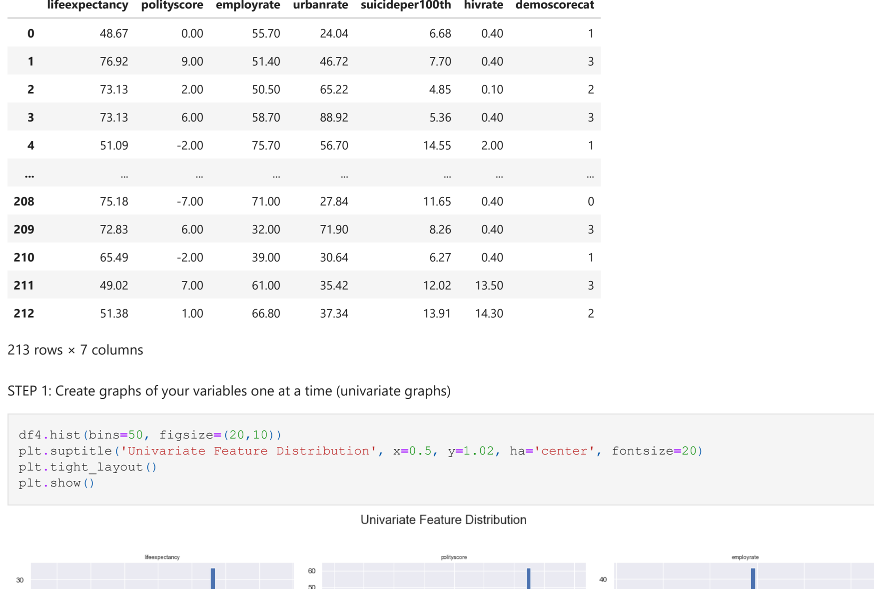
Employment rate influence urban rates.

In [45]:
```
df4.columns
```

Out[45]:
```
Index(['lifeexpectancy', 'polityscore', 'employrate', 'urbanrate', 'suicideper100th', 'hivrate', 'democsoreca
t'], dtype='object')
```

In [46]:
```
# Plot 4 rows and 1 column (can be expanded)

fig, ax = plt.subplots(2,1, sharex=False, figsize=(16,16))
#fig.suptitle('Main Title')


sns.barplot(x="democscorecat", y="lifeexpectancy", data=df4, ax=ax[0], ci=None)
ax[0].set_title('Relationship on Polity scores with life expectancy')
#ax[0].tick_params('x', labelrotation=45)
ax[0].set_xlabel("Polity Scores")
ax[0].set_ylabel("Life Expectancy")

sns.scatterplot(x="employrate", y="urbanrate", data=df4, ax=ax[1])
ax[1].set_title('Total Employees versus Urban Population')
#ax[1].tick_params('x', labelrotation=45)
ax[1].set_xlabel("Total Employees")
ax[1].set_ylabel("Urban Population")

plt.show()
```





Pairplots

In [47]:
```
plt.figure(figsize=(20,20))
plt.suptitle('Pairplots of features', x=0.5, y=1.02, ha='center', fontsize=20)
sns.pairplot(df4)
plt.show()
```

```
<Figure size 1440x1440 with 0 Axes>
```

The first graph shows that the higher the Polity Score, the life expectancy has improved.

The second graph shows no relationship between total employees with urban population.
