In [1]:
```
'''
Intro: In the following series of cells I will explore atlas data to compare GDP around the world.
I will be paying particular attention to Nations that have pledged themselves to the One Belt, One Road Initiat
ive,
also known as the Belt and Road Initiative (BRI), by signing an official Memorandum of Understanding.

Furthermore, I will be comparing nations that were rated poorly on the 2019 World justice Project Rule of Law i
ndex
as well as the AI Global Surveillance Index to draw comparisons and derive insights.

Predictions: I predict that Nations ranked poorly on these two indeces are also likely to be authoritatian regi
mes that
are subscribing to oppressive surveillance meausures using technology acquired as part of the Belt and Road Ini
tiative
'''
```

Out[1]:
```
'\nIntro: In the following series of cells I will explore atlas data to compare GDP around the world. \nI wil
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Furthermore, I will be comparing nations that were rated poorly on the 2019 World justice Project Rule of Law
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I predict that Nations ranked poorly on these two indeces are also likely to be authoritatian regimes that\na
re subscribing to oppressive surveillance meausures using technology acquired as part of the Belt and Road In
itiative\n'
```

In [2]:
```
# Import libraries
import requests
import bs4
from bs4 import BeautifulSoup
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [3]:
```
atlas_result = requests.get("https://www.worldatlas.com/aatlas/ctycodes.htm")
```

HTML Data Exploration: World Atlas Data

In [4]:
```
# Status: Successful
print(atlas_result.status_code)
```

```
200
```

In [5]:
```
print(atlas_result.headers)
```

```
{'Server': 'nginx/1.13.12', 'Content-Type': 'text/html; charset=utf-8', 'Transfer-Encoding': 'chunked', 'Conn
ection': 'keep-alive', 'X-Powered-By': 'PHP/7.3.5', 'X-Content-Type-Options': 'nosniff', 'X-XSS-Protection':
'1; mode=block', 'X-Frame-Options': 'SAMEORIGIN', 'Date': 'Tue, 02 Jun 2020 00:59:10 GMT', 'X-Page-Speed': '
1.13.35.2-0', 'Cache-Control': 'max-age=0, no-cache', 'Content-Encoding': 'gzip'}
```

In [6]:
```
atlas_src = atlas_result.content
```

In [7]:
```
print(atlas_src)
```

```
b'<!DOCTYPE html>\n<html lang="en">\n<head>\n<title>2-Letter, 3-Letter, Country Codes for All Countries in th
e World</title> <meta charset="utf-8">\n<meta name="description" content="2-letter country codes, 3-letter co
untry codes and a world atlas of facts flags and maps including every continent, country, dependency, exotic
destination, island, major city, ocean, province, state &amp; territory on the planet!">\n<meta property="fb:
app_id" content="1534891833401557">\n<meta property="fb:admins" content="518129666">\n<meta property="fb:admi
ns" content="100004698243421">\n<meta property="fb:pages" content="150031197968">\n<meta name="viewport" cont
ent="width=device-width, initial-scale=1">\n<meta name="msvalidate.01" content="88D149050818A728069F2C509B73C
38B"/>\n<link rel="dns-prefetch" href="//tagan.adlightning.com">\n<link rel="preload" href="/javascript/lazyL
oading.min.js" as="script">\n<link rel="preload" href="/javascript/menu.min.js?version=2" as="script">\n<link
rel="preload" href="/javascript/functions-desktop.js?1002" as="script">\n<link href="https://www.worldatlas.c
om/aatlas/ctycodes.htm" rel="canonical">\n<script src="//ajax.googleapis.com/ajax/libs/jquery/1.11.3/jquery.m
in.js"></script>\n<script>\n            var isMobile = !1;\n                             function setupImageMa
pSizes(){var a=document.getElementById("mapCont-lv1")||null,b=document.getElementById("image-map-left")||nul
l,c=document.getElementById("image-map-right")||null;if(null!==b&&null!==c&&a){var d=a.clientWidth,e=382;a.cl
assName&&/(^|\\s)wide(\\s|$)/.test(a.className)&&(e=500);var f=b.getAttribute("width"),a=c.getAttribute("widt
h"),b=b.getAttribute("height"),c=c.getAttribute("height");0!=b&&0!=c&&(f/=b,a/=c,d=Math.min(Math.floor((d-3
0)/(f+a)),e),e=Math.floor(f*d),a=Math.floor(a*d),document.getElementById("mapLeft").style.width=e+"px",docume
nt.getElementById("mapRight").style.width=a+"px",document.getElementById("mapLeft").style.height=document.get
ElementById("mapRight").height=d+"px",document.getElementById("mapLeft").style.display="block",document.getEl
ementById("mapRight").style.display="block")}}\n                            function setupImageMapSizes2(){ v
ar a=document.getElementById("mapCont-lv1")||null,b=document.getElementById("image-map-left")||null,c=documen
t.getElementById("image-map-right")||null;if(null!==b&&null!==c&&a){var d=a.clientWidth,e=720;var f=b.getAttr
ibute("width"),b=b.getAttribute("height");0!=b&&(f/=b,d=Math.min(Math.floor((d)/(f)),e),e=Math.floor(f*d),a=M
ath.floor(a*d),document.getElementById("mapLeft").style.width=e+"px",document.getElementById("mapRight").heig
ht=d+"px",document.getElementById("mapLeft").style.display="block",document.getElementById("mapRight").style.
display="block")}}\n        </script>\n<link href="/style/desktop/desktop.css?id=100230" rel="stylesheet" typ
e="text/css">\n<link href="/style/desktop/media.css?id=100230" rel="stylesheet" type="text/css">\n<link rel="
icon" href="/favicon.png" type="image/x-icon">\n<script>\n            (function(i,s,o,g,r,a,m){i[\'GoogleAnal
yticsObject\']=r;i[r]=i[r]||function(){\n            (i[r].q=i[r].q||[]).push(arguments)},i[r].l=1*new Date
();a=s.createElement(o),\n            m=s.getElementsByTagName(o)[0];a.async=1;a.src=g;m.parentNode.insertBef
ore(a,m)\n            })(window,document,\'script\',\'//www.google-analytics.com/analytics.js\',\'ga\');\n
ga(\'create\', \'UA-54278971-1\', \'auto\');\n    \n            ga(\'set\', \'dimension1\', \'true\');\nga(\'
set\', \'contentGroup1\', \'Legacy Content\');\nga(\'set\', \'contentGroup2\', \'Reference/Miscellaneous - Le
gacy\');\n            ga(\'send\', \'pageview\');\n        </script>\n<script async src="//js-sec.indexww.com
/ht/p/185608-236800388660207.js"></script>\n<script async src="//cdn.districtm.ca/merge/merge.v4.2.103743.js"
></script>\n<script async src=\'https://securepubads.g.doubleclick.net/tag/js/gpt.js\'></script>\n<script>\n
function reloadAd() {\n                googletag.pubads().refresh([reloadSlot], {changeCorrelator: tru
e});\n            \t}\n            </script>\n<script>\n            dfpAdSlots = [\n
{\n                 slotID: \'div-gpt-ad-1466105005014-0\',\n                 slotName: \'/60277011
/WA_Undertone_PageGrab\',\n                 sizes: [[1, 1]]\n                 },\n
{\n                 slotID: \'div-gpt-ad-1534784194224-0\',\n                 slotName: \'/
60277011/WA_Undertone_PageGrab_2.0\',\n                 sizes: [[1, 1]]\n                 },\
n                 \n\t\t\t\t                 \n                 \n                 {\n
slotID: \'div-gpt-ad-1466712522205-0\',\n                 slotName: \'/60277011/WA_Undertone_Billboard\',\n
sizes: [[970, 250]]\n                 },\n            \n                 {\n    slotID: \'div-gpt-ad-1463171380
981-2\',\n    slotName: \'/60277011/WA_D_Countries_InContent1_300x250\',\n    sizes: [[300, 250]]\n},\n{\n
slotID: \'div-gpt-ad-1463171380981-3\',\n    slotName: \'/60277011/WA_D_Countries_InContent2_300x250\',\n
```

In [8]:
```
atlas_soup = BeautifulSoup(atlas_src, 'lxml')
```

In [9]:
```
atlas_tables = atlas_soup.find_all("table")
```

In [10]:
```
# Table Contents
tbody = atlas_soup.find_all("tbody")
```

In [11]:
```
# View of the individual row elements in the countries table
for tr in tbody:
    for td in tr:
        if type(td) == bs4.element.Tag:
            print(td.text)
    print('\n')
```

```
COUNTRY A2 (ISO) A3 (UN) NUM (UN) DIALING CODE
Afghanistan AF AFG 4 93
Albania AL ALB 8 355
Algeria DZ DZA 12 213
American Samoa AS ASM 16 1-684
Andorra AD AND 20 376
Angola AO AGO 24 244
Anguilla AI AIA 660 1-264
Antarctica AQ ATA 10 672
Antigua and Barbuda AG ATG 28 1-268
Argentina AR ARG 32 54
Armenia AM ARM 51 374
Aruba AW ABW 533 297
Australia AU AUS 36 61
Austria AT AUT 40 43
Azerbaijan AZ AZE 31 994
Bahamas BS BHS 44 1-242
Bahrain BH BHR 48 973
Bangladesh BD BGD 50 880
Barbados BB BRB 52 1-246
Belarus BY BLR 112 375
Belgium BE BEL 56 32
Belize BZ BLZ 84 501
Benin BJ BEN 204 229
Bermuda BM BMU 60 1-441
Bhutan BT BTN 64 975
Bolivia BO BOL 68 591
Bonaire BQ BES 535 599
Bosnia and Herzegovina BA BIH 70 387
Botswana BW BWA 72 267
Bouvet Island BV BVT 74 47
Brazil BR BRA 76 55
British Indian Ocean Territory IO IOT 86 246
Brunei Darussalam BN BRN 96 673
Bulgaria BG BGR 100 359
Burkina Faso BF BFA 854 226
Burundi BI BDI 108 257
Cambodia KH KHM 116 855
Cameroon CM CMR 120 237
Canada CA CAN 124 1
Cape Verde CV CPV 132 238
Cayman Islands KY CYM 136 1-345
Central African Republic CF CAF 140 236
Chad TD TCD 148 235
Chile CL CHL 152 56
China CN CHN 156 86
Christmas Island CX CXR 162 61
```

In [12]:
```
# Placing table contents from atlas_soup into a Pandas DataFrame
atlas_df = pd.read_html(str(atlas_tables), header=0)[0]
```

In [13]:
```
atlas_df.head()
```

Out[13]:

	COUNTRY	A2 (ISO)	A3 (UN)	NUM (UN)	DIALING CODE
0	Afghanistan	AF	AFG	4	93
1	Albania	AL	ALB	8	355
2	Algeria	DZ	DZA	12	213
3	American Samoa	AS	ASM	16	1-684
4	Andorra	AD	AND	20	376

In [14]:
```
# Eliminating Unnecessary columns
atlas_df.drop(columns=['A2 (ISO)','A3 (UN)','NUM (UN)','DIALING CODE'], inplace=True)
```

In [15]:
```
# Atlas Final
atlas_df.head()
```

Out[15]:

	COUNTRY
0	Afghanistan
1	Albania
2	Algeria
3	American Samoa
4	Andorra

In [16]:
```
# Saving for later use
atlas_df.to_excel('data/atlas_countries_and_codes.xlsx', index=False)
```

Second Serving of Soup Data:

In [17]:
```
# New Soup - BRI countries
# Primary Source (In Chinese): https://www.yidaiyilu.gov.cn/info/iList.jsp?tm_id=126&cat_id=10122&info_id=77298
bri_result = requests.get("https://green-bri.org/countries-of-the-belt-and-road-initiative-bri") # secondary so
urce
bri_src = bri_result.content
bri_soup = BeautifulSoup(bri_src, 'lxml')
```

In [18]:
```
bri_tables = bri_soup.find_all("table")
```

In [19]:
```
bri_df = pd.read_html(str(bri_tables), header=0)[0]
```

In [20]:
```
# Quick Peak at the last 5 rows in the table
bri_df.tail()
```

Out[20]:

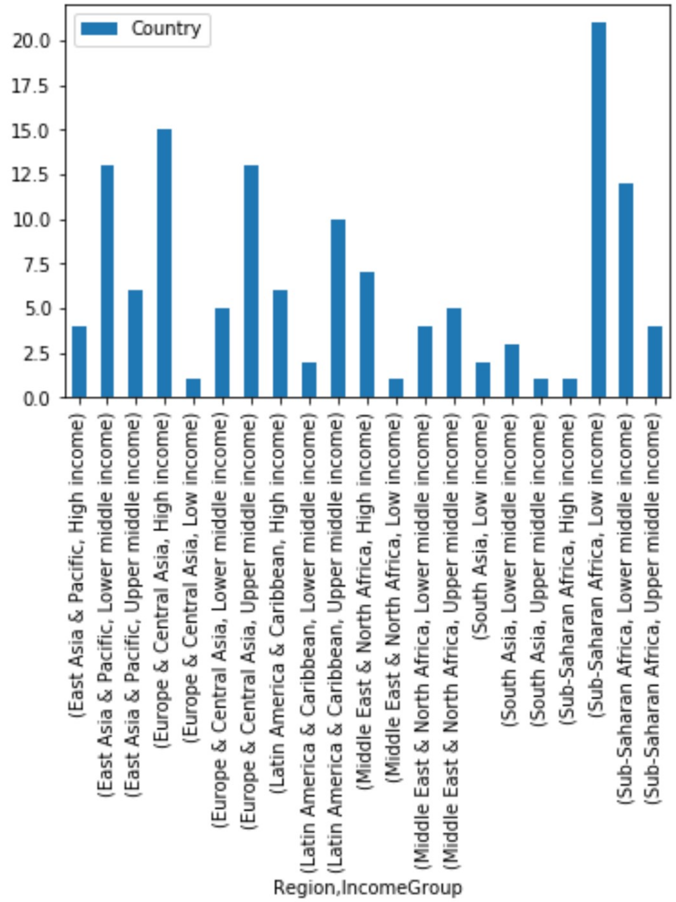
	Country	Region	IncomeGroup
133	Venezuela, RB	Latin America & Caribbean	Upper middle income
134	Vietnam	East Asia & Pacific	Lower middle income
135	Yemen, Rep.	Middle East & North Africa	Low income
136	Zambia	Sub-Saharan Africa	Lower middle income
137	Zimbabwe	Sub-Saharan Africa	Low income

In [21]:
```
# Preparing Histogram
num_bins=len(bri_df['Region'].unique())
num_bins
```

Out[21]: 6

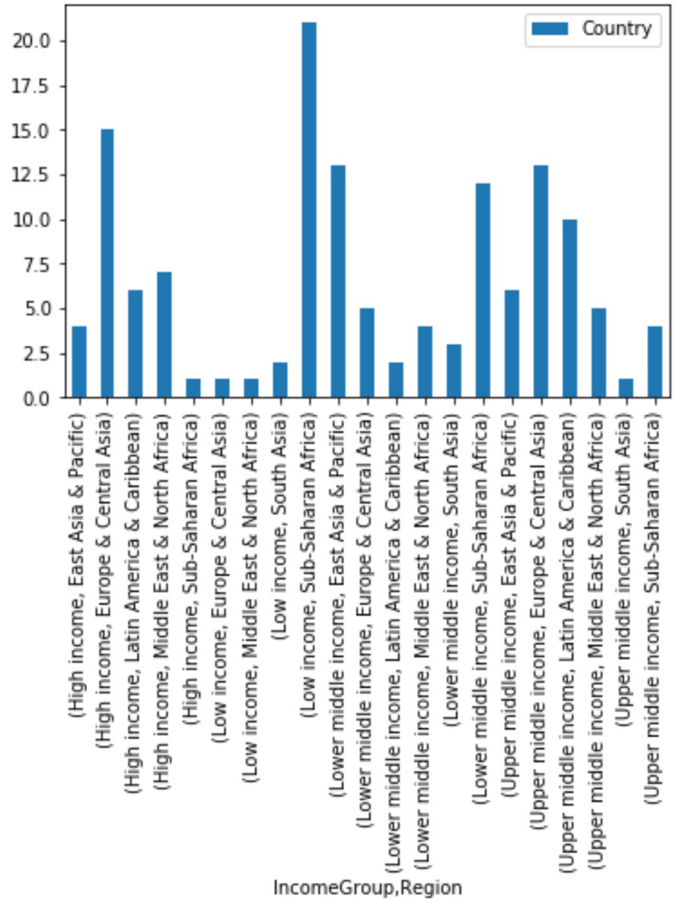
In [22]:
```
# Sorted by Region, subdivided by income group
bri_df.groupby(['Region','IncomeGroup']).count().plot(kind='bar')
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x1d59e1f78d0>



In [23]:
```
# Sorted by income groups, subdivided by region
bri_df.groupby(['IncomeGroup','Region']).count().plot(kind='bar')
```

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x1d59e4da550>



In [24]:
```
# Isolating the countries column to combine with atlas data
bri_countries = bri_df.drop(columns=['Region','IncomeGroup'])
# First 5 rows in the table
bri_countries.head()
```

Out[24]:

	Country
0	Afghanistan
1	Albania
2	Algeria
3	Angola
4	Antigua and Barbuda

Uniting the two new DataFrames:

In [25]:
```
# Joining the country col from the Atlas df and the Country col
# from the BRI df to determine BRI membership around the world
countries_mega_df = pd.concat([atlas_df, bri_countries], axis=1, sort=False)
```

In [26]:
```
# First 5 rows in the table
countries_mega_df.head()
```

Out[26]:

	COUNTRY	Country
0	Afghanistan	Afghanistan
1	Albania	Albania
2	Algeria	Algeria
3	American Samoa	Angola
4	Andorra	Antigua and Barbuda

Data Cleaning Phase:

In [27]:
```
countries_mega_df.rename(columns={'Country': 'BRI Countries'}, inplace=True)
```

In [28]:
```
countries_mega_df.rename(columns={'COUNTRY': 'Country'}, inplace=True)
```

In [29]:
```
# First 5 rows in the table
countries_mega_df.head()
```

Out[29]:

	Country	BRI Countries
0	Afghanistan	Afghanistan
1	Albania	Albania
2	Algeria	Algeria
3	American Samoa	Angola
4	Andorra	Antigua and Barbuda

In [30]:
```
# Merging into a single iterable string
stringList = ' '.join([str(item) for item in countries_mega_df['BRI Countries'].dropna(axis=0)])
```

In [31]:
```
stringList
```

Out[31]:
```
"Afghanistan Albania Algeria Angola Antigua and Barbuda Armenia Austria* Azerbaijan Bahrain Bangladesh Barbad
os Belarus Benin* Bolivia Bosnia and Herzegovina Brunei Darussalam Bulgaria Burundi Cabo Verde Cambodia Camer
oon Chad Chile China Cook Islands Comoros* Congo, Rep.* Costa Rica Côte d'Ivoire Croatia Cuba Cyprus Czech Re
public Djibouti Dominica* Ecuador Egypt, Arab Rep. El Salvador Equatorial Guinea Estonia Ethiopia Fiji Gabon
Gambia, The Georgia Ghana Greece Grenada Guinea Guyana Hungary Indonesia Iran, Islamic Rep. Iraq Italy Jamaic
a Kazakhstan Kenya Kiribati Korea, Rep. Kuwait Kyrgyz Republic Lao PDR Latvia Lebanon Lesotho Liberia Libya L
ithuania Luxembourg Madagascar Malaysia Maldives Mali Malta Mauritania Micronesia, Fed. Sts. Moldova Mongolia
Montenegro Morocco Mozambique Myanmar Namibia Nepal New Zealand Niger* Nigeria Niue North Macedonia Oman Paki
stan Panama Papua New Guinea Peru Philippines Poland Portugal Qatar Romania Russian Federation* Rwanda Samoa
Saudi Arabia Senegal Serbia Seychelles Sierra Leone Singapore Slovak Republic Slovenia Solomon Islands Somali
a South Africa South Sudan Sri Lanka Sudan Suriname Tajikistan Tanzania Thailand Timor-Leste Togo Tonga Trini
dad and Tobago Tunisia Turkey Uganda Ukraine United Arab Emirates Uruguay Uzbekistan Vanuatu Venezuela, RB Vi
etnam Yemen, Rep. Zambia Zimbabwe"
```

In [32]:
```
# Attempt to distinguish countries on the list of BRI subscribers and Countries not on the BRI list
#def separate(string, list)
temp = []
for i in countries_mega_df['Country']:
    if (i in stringList):
        print(i)
        print(' Was in the list')
    else:
        temp.append(i)
        print(i)
        print(' Was not in the list')
        continue
```

```
Afghanistan
 Was in the list
Albania
 Was in the list
Algeria
 Was in the list
American Samoa
 Was not in the list
Andorra
 Was not in the list
Angola
 Was in the list
Anguilla
 Was not in the list
Antarctica
 Was not in the list
Antigua and Barbuda
 Was in the list
Argentina
 Was not in the list
Armenia
 Was in the list
Aruba
 Was not in the list
Australia
 Was not in the list
Austria
 Was in the list
Azerbaijan
 Was in the list
Bahamas
 Was not in the list
Bahrain
 Was in the list
Bangladesh
 Was in the list
Barbados
 Was in the list
Belarus
 Was in the list
Belgium
 Was not in the list
Belize
 Was not in the list
Benin
 Was in the list
Bermuda
```

In [33]:
```
countries_mega_df['Non-BRI Countries'] = pd.Series(temp)
```

In [34]:
```
# First 5 rows in the table
countries_mega_df.head()
```

Out[34]:

	Country	BRI Countries	Non-BRI Countries
0	Afghanistan	Afghanistan	American Samoa
1	Albania	Albania	Andorra
2	Algeria	Algeria	Anguilla
3	American Samoa	Angola	Antarctica
4	Andorra	Antigua and Barbuda	Argentina

In [35]:
```
# Assigning a numeric BRI status indicator:
# (Subscribers and Non-Subscribers)
status = []
for country in countries_mega_df['Country']:
    if country in stringList:
        status.append(1)
    else:
        status.append(0)
countries_mega_df['BRI Status'] = status
```

In [36]:
```
countries_mega_df.head()
```

Out[36]:

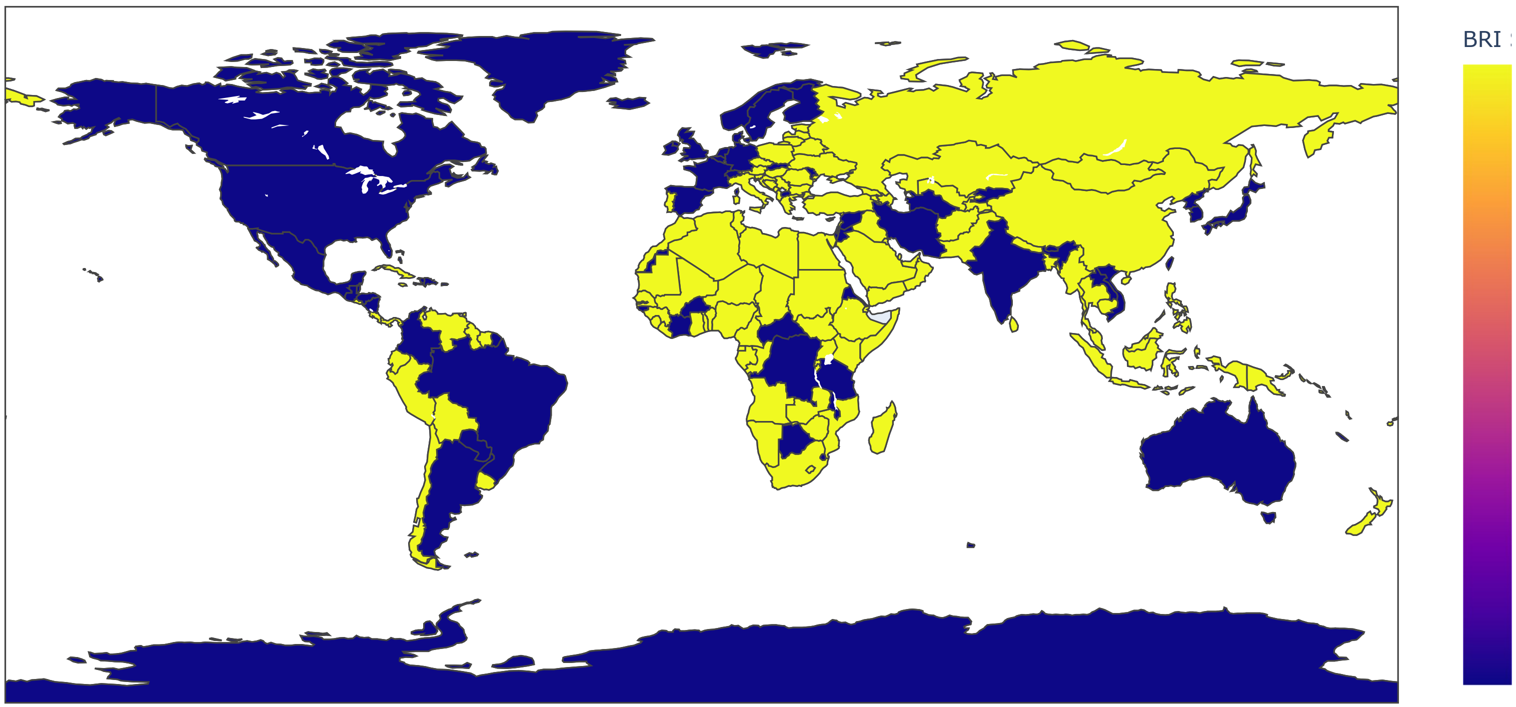
	Country	BRI Countries	Non-BRI Countries	BRI Status
0	Afghanistan	Afghanistan	American Samoa	1
1	Albania	Albania	Andorra	1
2	Algeria	Algeria	Anguilla	1
3	American Samoa	Angola	Antarctica	0
4	Andorra	Antigua and Barbuda	Argentina	0

In [37]:
```
# Map of Countries according to thier membership status in the Belt and road Initiative as of April 19, 2019
import plotly.express as px

geo_df = countries_mega_df
fig = px.choropleth(geo_df, locations="Country",
                    color="BRI Status", # lifeExp is a column of gapminder
                    hover_name="Country", # column to add to hover information
                    locationmode='country names')

fig.update_layout(title_text='2019 Belt and Road Intitiative Subscriber Nations')
fig.show()
```

2019 Belt and Road Intitiative Subscriber Nations



Third Serving of Soup GDP - 2017:

In [38]:
```
gdp_result = requests.get("https://www.worldometers.info/gdp/gdp-by-country/")
gdp_src = gdp_result.content
gdp_soup = BeautifulSoup(gdp_src, 'lxml')
gdp_tables = gdp_soup.find_all("table")
```

In [39]:
```
# From HTML Tables to DataFrame: Nominal GDP for 2017
gdp_df = pd.read_html(str(gdp_tables), header=0)[0]
# First 5 rows in the table
gdp_df.head()
```

Out[39]:

	#	Country	GDP (nominal, 2017)	GDP (abbrev.)	GDP growth	Population (2017)	GDP per capita	Share of World GDP
0	1	United States	$19,485,394,000,000	$19.485 trillion	2.27%	325084756	$59,939	24.08%
1	2	China	$12,237,700,479,375	$12.238 trillion	6.90%	1421021791	$8,612	15.12%
2	3	Japan	$4,872,415,104,315	$4.872 trillion	1.71%	127502725	$38,214	6.02%
3	4	Germany	$3,693,204,332,230	$3.693 trillion	2.22%	82658409	$44,680	4.56%
4	5	India	$2,650,725,335,364	$2.651 trillion	6.68%	1338676785	$1,980	3.28%

In [40]:
```
bri_df0 = bri_df.set_index('Country')
gdp_df0 = gdp_df.set_index('Country')
```

In [41]:
```
bri_gdp_df = gdp_df0.join(other=[bri_df0])
```

In [42]:
```
bri_gdp_df.head()
```

Out[42]:

Country	#	GDP (nominal, 2017)	GDP (abbrev.)	GDP growth	Population (2017)	GDP per capita	Share of World GDP	Region	IncomeGroup
United States	1	$19,485,394,000,000	$19.485 trillion	2.27%	325084756	$59,939	24.08%	NaN	NaN
China	2	$12,237,700,479,375	$12.238 trillion	6.90%	1421021791	$8,612	15.12%	East Asia & Pacific	Upper middle income
Japan	3	$4,872,415,104,315	$4.872 trillion	1.71%	127502725	$38,214	6.02%	NaN	NaN
Germany	4	$3,693,204,332,230	$3.693 trillion	2.22%	82658409	$44,680	4.56%	NaN	NaN
India	5	$2,650,725,335,364	$2.651 trillion	6.68%	1338676785	$1,980	3.28%	NaN	NaN

In [43]:
```
bri_gdp_df = bri_gdp_df.dropna(axis=0)
bri_gdp_df.head()
```

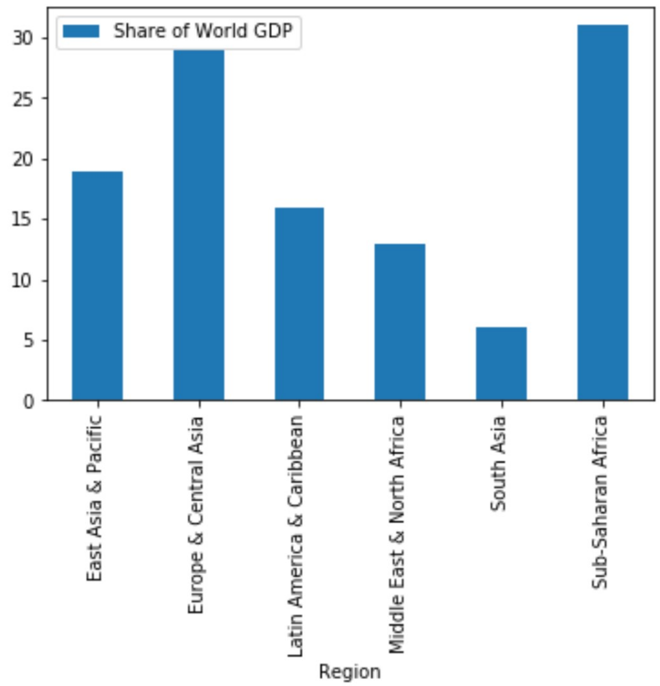
Out[43]:

Country	#	GDP (nominal, 2017)	GDP (abbrev.)	GDP growth	Population (2017)	GDP per capita	Share of World GDP	Region	IncomeGroup
China	2	$12,237,700,479,375	$12.238 trillion	6.90%	1421021791	$8,612	15.12%	East Asia & Pacific	Upper middle income
Italy	9	$1,943,835,376,342	$1.944 trillion	1.50%	60673701	$32,038	2.40%	Europe & Central Asia	High income
Indonesia	16	$1,015,420,587,285	$1.015 trillion	5.07%	264650963	$3,837	1.25%	East Asia & Pacific	Lower middle income
Turkey	17	$851,549,299,635	$852 billion	7.44%	81116450	$10,498	1.05%	Europe & Central Asia	Upper middle income
Saudi Arabia	19	$686,738,400,000	$687 billion	-0.86%	33101179	$20,747	0.85%	Middle East & North Africa	High income

In [44]:
```
bri_gdp_df1 = bri_gdp_df.drop(columns=['#','GDP (nominal, 2017)','GDP growth','Population (2017)','IncomeGroup
','GDP (abbrev.)','GDP per capita'])
```

In [45]:
```
bri_gdp_df1.groupby(['Region']).count().plot(kind='bar')
```

Out[45]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d5a07d8160>
```



Fourth Serving of Soup GDP - 2019:

In [46]:
```
# Estimated Projections of World GDP for 2019

gdp_2019_result = requests.get("http://www.statisticstimes.com/economy/gdp-indicators-2019.php")
gdp_2019_src = gdp_2019_result.content
gdp_2019_soup = BeautifulSoup(gdp_2019_src, 'lxml')
gdp_2019_tables = gdp_2019_soup.find_all("table")
```

In [47]:
```
# From HTML Tables to DataFrame: Estimated GDP for 2019
gdp_2019_df = pd.read_html(str(gdp_2019_tables), header=1)[1]
# gdp_2019_df.drop(gdp_2019_df.index[[0,195]], inplace=True)
# gdp_2019_df.sort_values(by=['GDP 2019 (billions of $).1'], inplace=True, ascending=False)
gdp_2019_df.head()
```

Out[47]:

	Country/Economy	Nominal	Rank	PPP	Rank.1	Nominal.1	Rank.2	PPP.1	Rank.3	2019	Rank.4
0	Pakistan	298.310	43	1219.720	25	1457	156	5958	140	4.005	74
1	Somalia	7.822	147	22.794	144	-	-	-	-	3.500	95
2	Afghanistan	21.074	115	76.491	104	577	183	2095	176	3.024	120
3	Albania	15.635	123	40.586	121	5448	102	14143	97	3.719	81
4	Algeria	200.171	55	693.109	36	4646	109	16086	88	2.708	131

In [48]:
```
# Data Cleaning - drop rows with null values
gdp_2019_df.dropna(inplace=True)
```

In [49]:
```
# Data Cleaning - drop column with "-" values
gdp_2019_df.drop(gdp_2019_df.index[[193]], inplace=True)
```

In [50]:
```
gdp_2019_df.rename(columns={'2019': 'GDP Growth (%) 2019'}, inplace=True)
```

In [51]:
```
gdp_2019_df.rename(columns={'Nominal': 'Estimated Nominal GDP 2019'}, inplace=True)
```

In [52]:
```
gdp_2019_df.rename(columns={'Rank': 'GDP Rank'}, inplace=True)
```

In [53]:
```
gdp_2019_df.head()
```

Out[53]:

	Country/Economy	Estimated Nominal GDP 2019	GDP Rank	PPP	Rank.1	Nominal.1	Rank.2	PPP.1	Rank.3	GDP Growth (%) 2019	Rank.4
0	Pakistan	298.310	43	1219.720	25	1457	156	5958	140	4.005	74
1	Somalia	7.822	147	22.794	144	-	-	-	-	3.500	95
2	Afghanistan	21.074	115	76.491	104	577	183	2095	176	3.024	120
3	Albania	15.635	123	40.586	121	5448	102	14143	97	3.719	81
4	Algeria	200.171	55	693.109	36	4646	109	16086	88	2.708	131

In [54]:
```
# Re-assigning according to Rank
gdp_2019_df.index =[int(x) for x in gdp_2019_df['GDP Rank']]
```

In [55]:
```
gdp_2019_df.index
```

Out[55]:
```
Int64Index([ 43, 147, 115, 123,  55,  62, 175,  30, 134, 166,
            ...
              7,   1,  77,  86, 181,  68,  46, 101, 108, 113],
           dtype='int64', length=193)
```

In [56]:
```
gdp_2019_df.head()
```

Out[56]:

	Country/Economy	Estimated Nominal GDP 2019	GDP Rank	PPP	Rank.1	Nominal.1	Rank.2	PPP.1	Rank.3	GDP Growth (%) 2019	Rank.4
43	Pakistan	298.310	43	1219.720	25	1457	156	5958	140	4.005	74
147	Somalia	7.822	147	22.794	144	-	-	-	-	3.500	95
115	Afghanistan	21.074	115	76.491	104	577	183	2095	176	3.024	120
123	Albania	15.635	123	40.586	121	5448	102	14143	97	3.719	81
55	Algeria	200.171	55	693.109	36	4646	109	16086	88	2.708	131

In [57]:
```
# Sorting new rank index
gdp_2019_df.sort_index(inplace=True)
```

In [58]:
```
# Eliminiating uneccessary columns
gdp_2019_df.drop(columns=['PPP','Rank.1','Nominal.1','Rank.2','PPP.1', 'Rank.3','Rank.4'], inplace=True)
```

In [59]:
```
#gdp_2019_df.reset_index()
gdp_2019_df.head()
```

Out[59]:

	Country/Economy	Estimated Nominal GDP 2019	GDP Rank	GDP Growth (%) 2019
1	United States	21482.410	1	2.541
2	China	14172.200	2	6.176
3	Japan	5220.570	3	0.943
4	Germany	4117.070	4	1.858
5	India	2957.720	5	7.436

Mapping the Global GDP for 2019

In [60]:
```
gdp_2019_df.describe()
```

Out[60]:

	Country/Economy	Estimated Nominal GDP 2019	GDP Rank	GDP Growth (%) 2019
count	193	193	193	193
unique	193	193	193	179
top	Saudi Arabia	26.004	90	5.000
freq	1	1	1	4

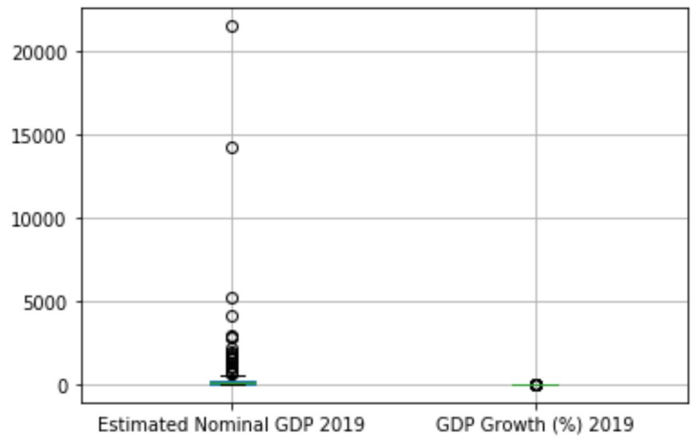
In [61]:
```
for col in gdp_2019_df:
    print(type(col))
```

```
<class 'str'>
<class 'str'>
<class 'str'>
<class 'str'>
```

In [62]:
```
gdp_2019_df[['Estimated Nominal GDP 2019', 'GDP Rank', 'GDP Growth (%) 2019']] = gdp_2019_df[['Estimated Nomina
l GDP 2019', 'GDP Rank', 'GDP Growth (%) 2019']].apply(pd.to_numeric)
```

In [63]:
```
# Two major Outliers: USA and China
gdp_2019_df.boxplot(column=['Estimated Nominal GDP 2019','GDP Growth (%) 2019'])
```

Out[63]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d5a07d6f98>
```

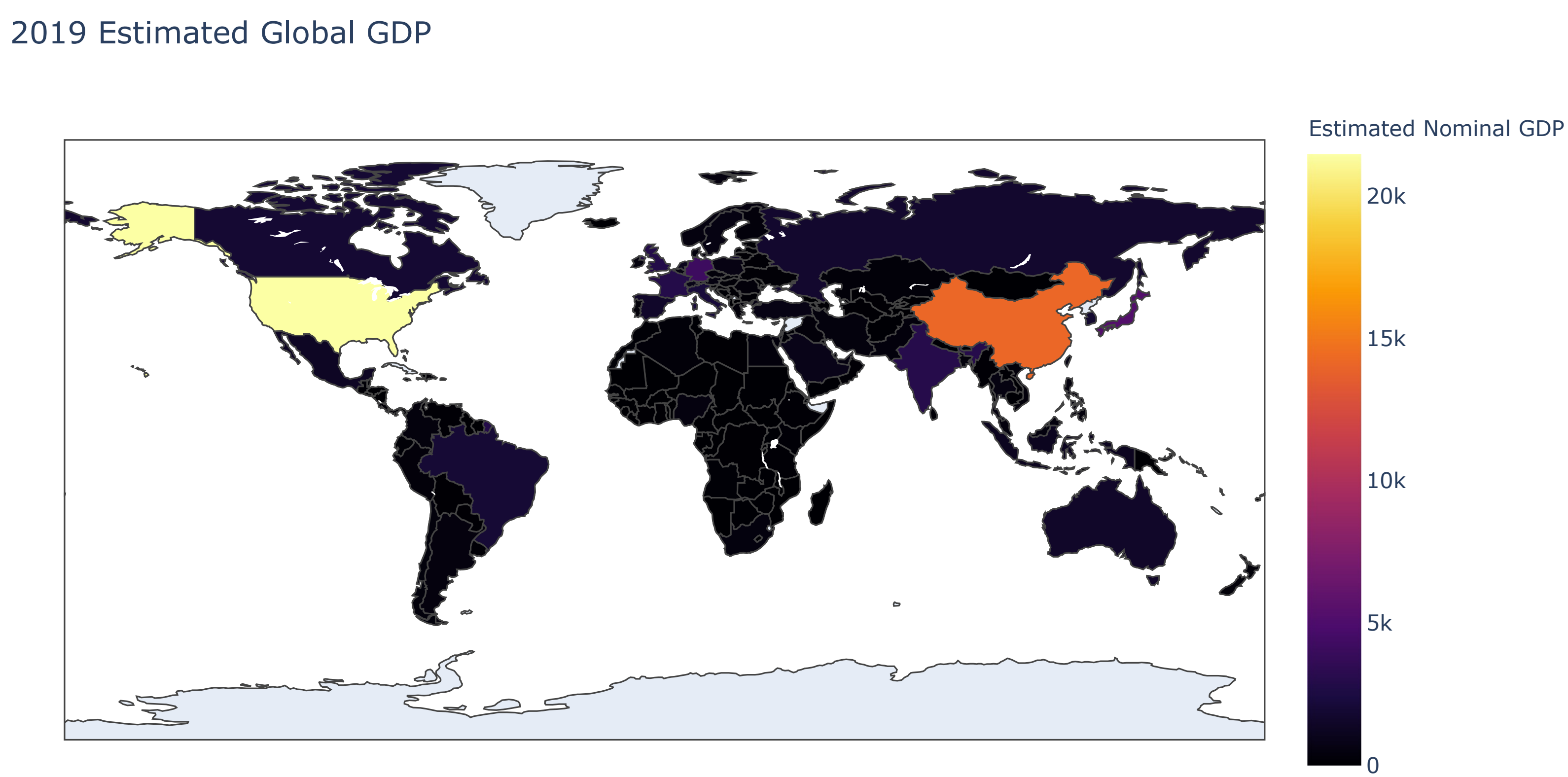


In [64]:
```
# Map of Countries according to thier Estimated GDP for 2019
import plotly.express as px

geo_df = gdp_2019_df

fig = px.choropleth(geo_df, locations="Country/Economy",
                    color="Estimated Nominal GDP 2019",
                    #range_color=(0,21500.000),# add a scale/color scheme
                    hover_name="GDP Growth (%) 2019",
                    color_continuous_scale='Inferno',# column to add to hover information
                    locationmode='country names')

fig.update_layout(title_text='2019 Estimated Global GDP')
fig.show()
```



Global Threats and Final Conclusions

In [65]:
```
# Hand-Crafted Excel Document of 30 lowest rated countries on the Global Surveillance Index
AI_df = pd.read_excel('data/Top 30 A.I. Global Surveillance Index Worst Offenders.xlsx', index=False)

# Data Source: https://carnegieendowment.org/2019/09/17/global-expansion-of-ai-surveillance-pub-79847
```

In [66]:
```
# Scores of Bolivia and Mexico were added for the sake of compatibility, these two are not amongst the top 30
AI_df.head()
```

Out[66]:

	Country	Agg. AIGS Score	(BRI) Participant	Types of AI Surveillance	Powered by Chinese Tech	Powered by American Tech
0	Saudi Arabia	0.97	1	3	1	1
1	Tajikistan	1.52	1	2	1	0
2	Uzbekistan	1.65	1	2	1	0
3	Bahrain	1.72	1	2	1	0
4	China	1.77	1	3	1	1

In [67]:
```
### Types of Surveillance refers to the use of:
# 1) Facial Recognition,
# 2) Smart Cities/Safe City Tech and
# 3) Smart Policing/Predictive Policing###
'''These Technologies all have tremendous potential to be used for good or ill purposes.
Utilization of this technology does not on its own indicate abuse, however
taken in consideration with other factors it may be be indicative of a risk of abuse.'''

### Agg. AIGS Score refers to a weighted aggregate score that takes into consideration
# a country's rank placement on the following indeces:
# 2018 Freedom in the World Index,
# 2018 EIU Democracy Index,
# And the V-Dem Electoral Democracy Index

'''More Information can be found at:
    https://carnegieendowment.org/2019/09/17/global-expansion-of-ai-surveillance-pub-79847'''
```

Out[67]:
```
'More Information can be found at:\n    https://carnegieendowment.org/2019/09/17/global-expansion-of-ai-surve
illance-pub-79847'
```

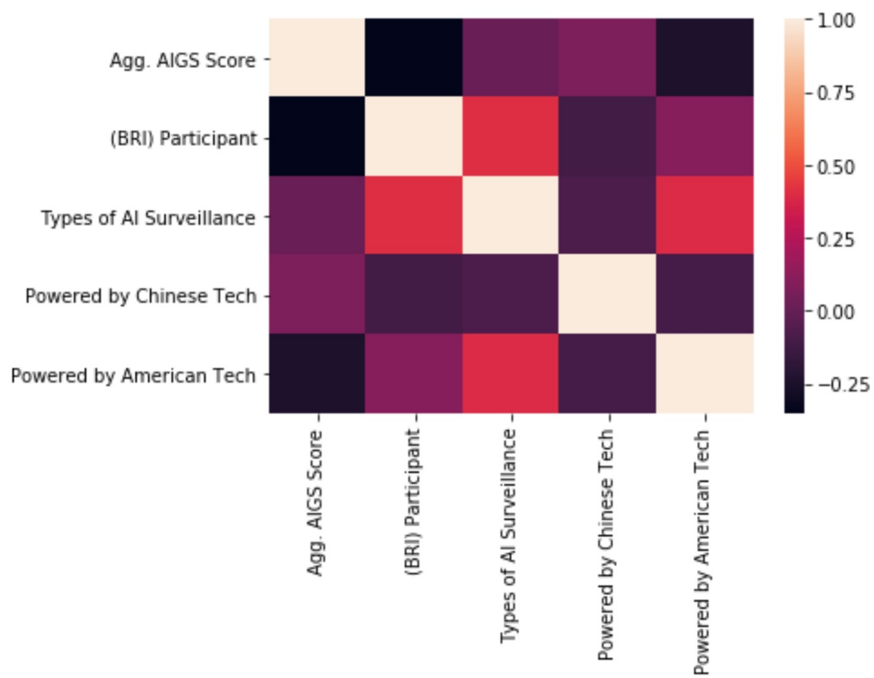
In [68]:
```
# Correlation Matrix of all data attributes and how they relate to one another
corr_mat = AI_df.corr()
corr_mat
```

Out[68]:

	Agg. AIGS Score	(BRI) Participant	Types of AI Surveillance	Powered by Chinese Tech	Powered by American Tech
Agg. AIGS Score	1.000000	-0.351355	0.015541	0.080290	-0.250020
(BRI) Participant	-0.351355	1.000000	0.408653	-0.111111	0.104447
Types of AI Surveillance	0.015541	0.408653	1.000000	-0.078731	0.393539
Powered by Chinese Tech	0.080290	-0.111111	-0.078731	1.000000	-0.104447
Powered by American Tech	-0.250020	0.104447	0.393539	-0.104447	1.000000

In [69]:
```
'''A Value of one indicates perfect correlation,
a value of 0 refers to a complete lack of a relationship,
and a negative value indicates an inverse relationship.'''
sns.heatmap(corr_mat)
```

Out[69]: <matplotlib.axes._subplots.AxesSubplot at 0x1d59aadf240>



In [70]:
```
#Source: https://worldjusticeproject.org/our-work/research-and-data/wjp-rule-law-index-2019
ROL_df = pd.read_excel('data/Rule of Law Index 30 Worst Offenders.xlsx', index=False)
```

In [71]:
```
ROL_df.head()
```

Out[71]:

	2016	2017 - 2018	2019
0	Venezuela	Venezuela	Venezuela
1	Cambodia	Cambodia	Cambodia
2	Afghanistan	Afghanistan	Congo
3	Egypt	Egypt	Afghanistan
4	Cameroon	Cameroon	Mauritania

In [72]:
```
# Top 30 Rule of Law offender Nations of 2019
ROL_df['Top 30 RoL Offendor Status'] = [1 for num in range(0,len(ROL_df[2019]))]
```

In [73]:
```
ROL_df.drop(columns=[2016,'2017 - 2018'], inplace=True)
```

In [74]:
```
ROL_df.head()
```

Out[74]:

	2019	Top 30 RoL Offendor Status
0	Venezuela	1
1	Cambodia	1
2	Congo	1
3	Afghanistan	1
4	Mauritania	1

Cleaning Data for BRI Nations

In [75]:
```
'''Of the 138 alleged BRI nations, the membership status of 7 countries is currently disputed.
These nations have neither confirmed nor denied claims of having signed a Memorandum of Understanding,
which is indicative of thier agreement to Join in the One Belt, One Road Initiative, also known as the
Belt and Road Initiative (BRI). These Nations are identified in the list of 138 countries by an '*'
symbol the right-hand side of thier Country Names. These disputed nations include: Austria, Benin, Comoros,
the Democratic Republic of Congo AKA Congo, Rep., Dominica, Niger, and The Russian Federation AKA Russia.

Note: For the sake of completeness, these 7 countries are also included.'''
```

Out[75]:
```
"Of the 138 alleged BRI nations, the membership status of 7 countries is currently disputed. \nThese nations
have neither confirmed nor denied claims of having signed a Memorandum of Understanding, \nwhich is indicativ
e of thier agreement to Join in the One Belt, One Road Initiative, also known as the\nBelt and Road Initiativ
e (BRI). These Nations are identified in the list of 138 countries by an '*' \nsymbol the right-hand side of
thier Country Names. These disputed nations include: Austria, Benin, Comoros,\nthe Democratic Republic of Con
go AKA Congo, Rep., Dominica, Niger, and The Russian Federation AKA Russia.\n\nNote: For the sake of complete
ness, these 7 countries are also included."
```

In [76]:
```
# Changing 'Venezuela, RB' to 'Venezuela' to match values in other tables
bri_df['Country'][133] = 'Venezuela'
bri_df['Country'][133]
```

Out[76]:
```
'Venezuela'
```

In [77]:
```
# Changing 'Congo, Rep' to 'Congo' to match values in other tables
bri_df['Country'][26] = 'Congo'
bri_df['Country'][26]
```

Out[77]:
```
'Congo'
```

In [78]:
```
# First Measure => Including disputed Nations; index values 6, 12, 25, 26, 34, 86, 100
# Eliminate Trailing '*' in bri_df['Country']
bri_df1 = bri_df
bri_df1['Country'][6] = bri_df1['Country'][6].rstrip('*')
bri_df1['Country'][12] = bri_df1['Country'][12].rstrip('*')
bri_df1['Country'][25] = bri_df1['Country'][25].rstrip('*')
bri_df1['Country'][26] = bri_df1['Country'][26].rstrip('*')
bri_df1['Country'][34] = bri_df1['Country'][34].rstrip('*')
bri_df1['Country'][86] = bri_df1['Country'][86].rstrip('*')
bri_df1['Country'][100] = bri_df1['Country'][100].rstrip('*')
bri_df1.head(15)
```

Out[78]:

	Country	Region	IncomeGroup
0	Afghanistan	South Asia	Low income
1	Albania	Europe & Central Asia	Upper middle income
2	Algeria	Middle East & North Africa	Upper middle income
3	Angola	Sub-Saharan Africa	Lower middle income
4	Antigua and Barbuda	Latin America & Caribbean	High income
5	Armenia	Europe & Central Asia	Upper middle income
6	Austria	Europe & Central Asia	High income
7	Azerbaijan	Europe & Central Asia	Upper middle income
8	Bahrain	Middle East & North Africa	High income
9	Bangladesh	South Asia	Lower middle income
10	Barbados	Latin America & Caribbean	High income
11	Belarus	Europe & Central Asia	Upper middle income
12	Benin	Sub-Saharan Africa	Low income
13	Bolivia	Latin America & Caribbean	Lower middle income
14	Bosnia and Herzegovina	Europe & Central Asia	Upper middle income

In [79]:
```
# Preparing the join-keys for the table Join
ROL_df.rename(columns={2019: 'Country'}, inplace=True)
#  AI_df already has column 'Country'
# bri_df already has column 'Country'
gdp_2019_df.rename(columns={'Country/Economy': 'Country'}, inplace=True)
```

In [80]:
```
# Changing 'Republic of Congo' to 'Congo' to match values in other tables
gdp_2019_df['Country'][26] = 'Congo'
gdp_2019_df['Country'][26]
```

```
C:\Users\Nazgul\AppData\Local\Continuum\anaconda3\lib\site-packages\ipykernel_launcher.py:2: SettingWithCopyW
arning:


A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view
-versus-copy
```

Out[80]:
```
'Congo'
```

In [81]:
```
# Set Country to Index for Joining (Join only allowed on index)
ROL_df1 = ROL_df.set_index('Country')
AI_df1 = AI_df.set_index('Country')
bri_df2 = bri_df1.set_index('Country')
gdp_2019_df1 = gdp_2019_df.set_index('Country')
ROL_df1.head()
```

Out[81]:

	Top 30 RoL Offendor Status
Country	
Venezuela	1
Cambodia	1
Congo	1
Afghanistan	1
Mauritania	1

In [82]:
```
# Save for After Prep Work is done:
Final_df1 = ROL_df1.join(other=[AI_df1, bri_df2, gdp_2019_df1])
```

In [83]:
```
Final_df1
```

Out[83]:

Country	Top 30 RoL Offendor Status	Agg. AIGS Score	(BRI) Participant	Types of AI Surveillance	Powered by Chinese Tech	Powered by American Tech	Region	IncomeGroup	Estimated Nominal GDP 2019	GDP Rank	GDP Growth (%) 2019
Venezuela	1	2.49	1.0	1.0	1.0	0.0	Latin America & Caribbean	Upper middle income	87.010	68.0	-5.000
Cambodia	1	NaN	NaN	NaN	NaN	NaN	East Asia & Pacific	Lower middle income	26.372	107.0	6.778
Congo	1	NaN	NaN	NaN	NaN	NaN	Sub-Saharan Africa	Lower middle income	469.661	26.0	2.150
Afghanistan	1	NaN	NaN	NaN	NaN	NaN	South Asia	Low income	21.074	115.0	3.024
Mauritania	1	NaN	NaN	NaN	NaN	NaN	Sub-Saharan Africa	Lower middle income	5.243	154.0	5.237
Egypt	1	2.56	1.0	3.0	1.0	1.0	NaN	NaN	298.153	44.0	5.464
Cameroon	1	NaN	NaN	NaN	NaN	NaN	Sub-Saharan Africa	Lower middle income	40.125	98.0	4.401
Bolivia	1	6.27	1.0	3.0	1.0	0.0	Latin America & Caribbean	Lower middle income	45.045	93.0	4.200
Ethiopia	1	NaN	NaN	NaN	NaN	NaN	Sub-Saharan Africa	Low income	88.170	67.0	8.494
Pakistan	1	4.44	1.0	3.0	1.0	0.0	South Asia	Lower middle income	298.310	43.0	4.005
Zimbabwe	1	3.18	0.0	2.0	1.0	0.0	Sub-Saharan Africa	Low income	21.630	113.0	4.202
Honduras	1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	24.496	111.0	3.600
Nicaragua	1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	13.626	132.0	-1.000
Uganda	1	4.18	1.0	2.0	1.0	0.0	Sub-Saharan Africa	Low income	29.869	104.0	6.105
Bangladesh	1	4.36	1.0	3.0	1.0	0.0	South Asia	Lower middle income	313.509	41.0	7.097
Angola	1	NaN	NaN	NaN	NaN	NaN	Sub-Saharan Africa	Lower middle income	110.186	62.0	3.055

In [84]:
```
# Filling Null Values with the average of the corresponding column
Final_df1['Agg. AIGS Score'].fillna(value=Final_df1['Agg. AIGS Score'].mean(), inplace=True)
Final_df1['(BRI) Participant'].fillna(value=1.0, inplace=True) # All in BRI 138 list except for Honduras and Ni
caragua;
# Niger is the only country amongst the disputed 7 that is included in this set
Final_df1['Types of AI Surveillance'].fillna(value=Final_df1['Types of AI Surveillance'].mean(), inplace=True)
Final_df1['Powered by Chinese Tech'].fillna(value=0.5, inplace=True) # Not confirmed one way or another so 50/5
0 chance of 1 or 0
Final_df1['Powered by American Tech'].fillna(value=0.5, inplace=True) # Not confirmed one way or another so 50/
50 chance of 1 or 0
```

In [85]:
```
Final_df1['(BRI) Participant'][12] = 0 # Honduras
Final_df1['(BRI) Participant'][12] = 0 # Nicaragua
```

```
C:\Users\Nazgul\AppData\Local\Continuum\anaconda3\lib\site-packages\ipykernel_launcher.py:1: SettingWithCopyW
arning:


A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view
-versus-copy

C:\Users\Nazgul\AppData\Local\Continuum\anaconda3\lib\site-packages\ipykernel_launcher.py:2: SettingWithCopyW
arning:


A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view
-versus-copy
```

In [86]:
```
Final_df1
```

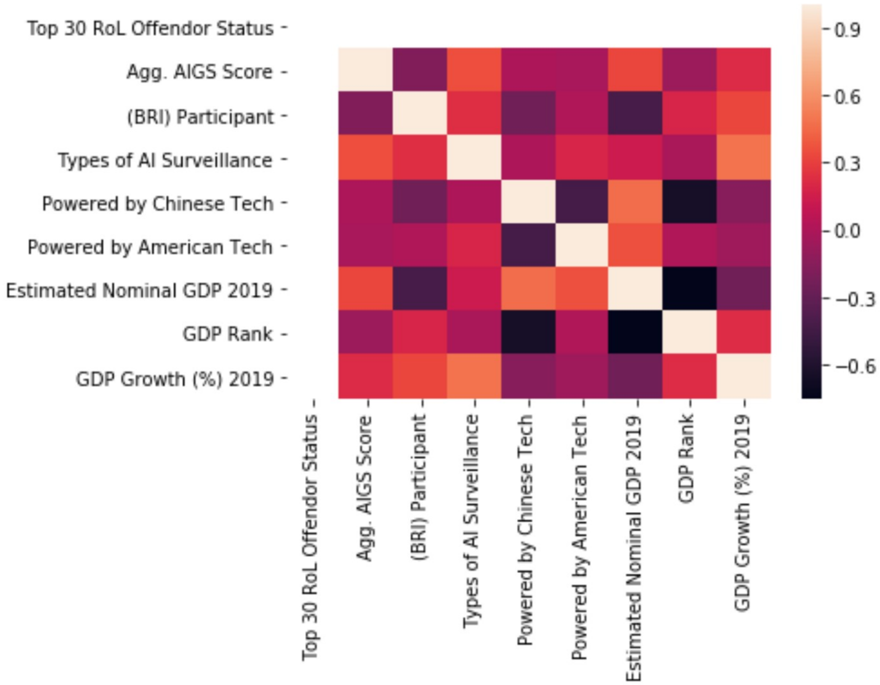
Out[86]:

Country	Top 30 RoL Offendor Status	Agg. AIGS Score	(BRI) Participant	Types of AI Surveillance	Powered by Chinese Tech	Powered by American Tech	Region	IncomeGroup	Estimated Nominal GDP 2019	GDP Rank	GDP Growth (%) 2019
Venezuela	1	2.490000	1.0	1.000000	1.0	0.0	Latin America & Caribbean	Upper middle income	87.010	68.0	-5.000
Cambodia	1	4.093077	1.0	2.384615	0.5	0.5	East Asia & Pacific	Lower middle income	26.372	107.0	6.778
Congo	1	4.093077	1.0	2.384615	0.5	0.5	Sub-Saharan Africa	Lower middle income	469.661	26.0	2.150
Afghanistan	1	4.093077	1.0	2.384615	0.5	0.5	South Asia	Low income	21.074	115.0	3.024
Mauritania	1	4.093077	1.0	2.384615	0.5	0.5	Sub-Saharan Africa	Lower middle income	5.243	154.0	5.237
Egypt	1	2.560000	1.0	3.000000	1.0	1.0	NaN	NaN	298.153	44.0	5.464
Cameroon	1	4.093077	1.0	2.384615	0.5	0.5	Sub-Saharan Africa	Lower middle income	40.125	98.0	4.401
Bolivia	1	6.270000	1.0	3.000000	1.0	0.0	Latin America & Caribbean	Lower middle income	45.045	93.0	4.200
Ethiopia	1	4.093077	1.0	2.384615	0.5	0.5	Sub-Saharan Africa	Low income	88.170	67.0	8.494
Pakistan	1	4.440000	1.0	3.000000	1.0	0.0	South Asia	Lower middle income	298.310	43.0	4.005
Zimbabwe	1	3.180000	0.0	2.000000	1.0	0.0	Sub-Saharan Africa	Low income	21.630	113.0	4.202
Honduras	1	4.093077	1.0	2.384615	0.5	0.5	NaN	NaN	24.496	111.0	3.600
Nicaragua	1	4.093077	0.0	2.384615	0.5	0.5	NaN	NaN	13.626	132.0	-1.000
Uganda	1	4.180000	1.0	2.000000	1.0	0.0	Sub-Saharan Africa	Low income	29.869	104.0	6.105
Bangladesh	1	4.360000	1.0	3.000000	1.0	0.0	South Asia	Lower middle income	313.509	41.0	7.097
Angola	1	4.093077	1.0	2.384615	0.5	0.5	Sub-Saharan	Lower middle	110.186	62.0	3.055

In [87]:
```
Final1_matrix = Final_df1.corr()
```

In [88]:
```
sns.heatmap(Final1_matrix)
```

Out[88]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d59e660668>
```



Findings:

In [89]:
```
#Amongst the 30 Worst Offendors on the Rule of Law Index, the following seem to be inversely correlated:
'''
High value in one relates to low value in the other:
    GDP Rank vs Estimated Nominal GDP for 2019, -> 'Smaller' Rank No. AKA Higher Ranked Countries have a larger
Nominal GDP
    GDP Rank vs Powered by Chinese Tech, -> Aside from a sizable handful of lower-income countries in Sub-Sahar
an Africa,
                                            Chinese Tech is most prevelant in countries that are high-ranked in
terms of GDP
    BRI Participation vs Estimated Nominal GDP 2019, -> Again, China Powering mostly low-income countries
    Powered by Chinese Tech vs Powered by American Tech, -> Most countries select one or the other but there is
overlap
    BRI Participation vs Agg. AIGS Score, -> BRI Participants are likely to have a lower score, indicating abus
e of AI
'''
#Amongst the 30 Worst Offendors on the Rule of Law Index, the following seem to be directly correlated:
'''
High value in one relates to high value in the other:
    GDP Growth vs Types of Surveillance, -> Rising countries are investing more heavily in Surveillance Tech
    GDP Growth vs BRI Participation, -> BRI participant nations are experiencing higher GDP growth rates in ter
ms of %
    Estimated Nominal GDP 2019 vs Powered by American Tech, -> High Income Nations are likely to buy American T
ech
    Estimated Nominal GDP 2019 vs Powered by Chinese Tech, -> High Income Nations are even more likely to buy C
hinese Tech
    Types of Surveillance vs Agg. AIGS Score, -> Nations with more variety of surveillance measures have slight
ly higher scores
'''
```

Out[89]:
```
'\nHigh value in one relates to high value in the other:\n    GDP Growth vs Types of Surveillance, -> Rising
countries are investing more heavily in Surveillance Tech\n    GDP Growth vs BRI Participation, -> BRI partic
ipant nations are experiencing higher GDP growth rates in terms of %\n    Estimated Nominal GDP 2019 vs Power
ed by American Tech, -> High Income Nations are likely to buy American Tech\n    Estimated Nominal GDP 2019 v
s Powered by Chinese Tech, -> High Income Nations are even more likely to buy Chinese Tech\n    Types of Surv
eillance vs Agg. AIGS Score, -> Nations with more variety of surveillance measures have slightly higher score
s\n'
```

In [90]:
```
# 30 Lowest rated countries on the Artificial Intelligence Global Surveillance (AIGS) Index
# Indicative of greatest levels of abuse of AI tech
Final_df2 = AI_df1.join(other=[bri_df2, gdp_2019_df1])
```

In [91]:
```
Final_df2
```

Out[91]:

Country	Agg. AIGS Score	(BRI) Participant	Types of AI Surveillance	Powered by Chinese Tech	Powered by American Tech	Region	IncomeGroup	Estimated Nominal GDP 2019	GDP Rank	GDP Growth (%) 2019
Saudi Arabia	0.97	1	3	1	1	Middle East & North Africa	High income	795.582	18.0	2.428
Tajikistan	1.52	1	2	1	0	Europe & Central Asia	Low income	7.577	149.0	5.000
Uzbekistan	1.65	1	2	1	0	Europe & Central Asia	Lower middle income	51.339	86.0	5.000
Bahrain	1.72	1	2	1	0	Middle East & North Africa	High income	41.607	97.0	2.585
China	1.77	1	3	1	1	East Asia & Pacific	Upper middle income	14172.200	2.0	6.176
United Arab Emirates	1.87	1	3	1	1	Middle East & North Africa	High income	455.587	27.0	3.662
Qatar	2.21	1	3	0	0	Middle East & North Africa	High income	204.306	54.0	2.816
Oman	2.41	1	2	1	1	Middle East & North Africa	High income	86.525	69.0	5.045
Laos	2.46	1	2	1	0	NaN	NaN	NaN	NaN	NaN
Venezuela	2.49	1	1	1	0	Latin America & Caribbean	Upper middle income	87.010	68.0	-5.000
Egypt	2.56	1	3	1	1	NaN	NaN	298.153	44.0	5.464
Russia	2.60	1	3	1	1	NaN	NaN	1649.210	12.0	1.797
Rwanda	2.75	1	1	1	0	Sub-Saharan Africa	Low income	10.532	142.0	7.800
Kazakhstan	3.01	1	3	1	1	Europe & Central Asia	Upper middle income	195.738	56.0	3.130
Thailand	3.08	1	2	1	0	East Asia & Pacific	Upper middle income	524.253	25.0	3.859
Zimbabwe	3.18	0	2	1	0	Sub-Saharan Africa	Low income	21.630	113.0	4.202
Algeria	3.32	0	1	1	0	Middle East & North Africa	Upper middle income	200.171	55.0	2.708
Iraq	3.36	1	2	1	0	Middle East & North Africa	Upper middle income	250.070	48.0	6.517
Iran	3.57	1	3	1	0	NaN	NaN	NaN	NaN	NaN

In [92]:
```
Final2_matrix = Final_df2.corr()
```

In [93]:
```
sns.heatmap(Final2_matrix, cmap="YlGnBu")
```

Out[93]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1d59ac4c2b0>
```

In [94]:
```
#Amongst the 30 Worst Offendors on the AI Global Surveillance Index, the following seem to be inversely correla
ted:
'''
High value in one relates to low value in the other:
    BRI Participant vs Agg. AIGS Score,
    GDP Rank vs Types of Surveillance, -> 'Smaller' Rank AKA Higher Ranked Nations have a larger variety of Sur
veillance measures
    GDP Rank vs Powered by American Tech, -> 'Smaller' Rank AKA Higher Ranked Nations are likely to be Powered
by American Tech
    GDP Rank vs Estimated Nominal GDP 2019, -> 'Smaller' Rank AKA Higher Ranked Nations have a larger estimated
Nominal GDP
    GDP Growth vs Powered by American Tech -> Countries Experiencing higher Growth Rates are more likely to hav
e purchased American Tech
'''
#Amongst the 30 Worst Offendors on the AI Global Surveillance Index, the following seem to be directly correlat
ed:
'''
High value in one relates to high value in the other:
    BRI Participation vs Types of Surveillance, -> BRI Participants are more likely to use various types of sur
veillance measures
    Powered by American Tech vs Types of Surveillance, -> Countries powered by American Tech are also likely to
use different types of surveillance measures
    Powered by American Tech vs Estimateed Nominal GDP 2019, -> Nations with High GDP are likely to buy America
n Tech
    GDP Rank vs GDP Growth, -> 'Larger' Rank AKA Low Ranked Nations are experience Higher Growth rates
'''
```

Out[94]:
```
"\nHigh value in one relates to high value in the other:\n    BRI Participation vs Types of Surveillance, ->
BRI Participants are more likely to use various types of surveillance measures\n    Powered by American Tech
vs Types of Surveillance, -> Countries powered by American Tech are also likely to use different types of sur
veillance measures\n    Powered by American Tech vs Estimateed Nominal GDP 2019, -> Nations with High GDP are
likely to buy American Tech\n    GDP Rank vs GDP Growth, -> 'Larger' Rank AKA Low Ranked Nations are experien
ce Higher Growth rates\n"
```