In [1]:
```python
import numpy as np
import pandas as pd
import matplotlib .pyplot as plt
from matplotlib import style
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

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

Out[2]:

	Rank	CCA3	Country/Territory	Capital	Continent	2022 Population	2020 Population	2015 Population	Popu
0	36	AFG	Afghanistan	Kabul	Asia	41128771	38972230	33753499	28
1	138	ALB	Albania	Tirana	Europe	2842321	2866849	2882481	29
2	34	DZA	Algeria	Algiers	Africa	44903225	43451666	39543154	358
3	213	ASM	American Samoa	Pago Pago	Oceania	44273	46189	51368	
4	203	AND	Andorra	Andorra la Vella	Europe	79824	77700	71746	
...	...	...	...	...	...	...	...	...	
229	226	WLF	Wallis and Futuna	Mata-Utu	Oceania	11572	11655	12182	
230	172	ESH	Western Sahara	El Aaiún	Africa	575986	556048	491824	4
231	46	YEM	Yemen	Sanaa	Asia	33696614	32284046	28516545	247
232	63	ZMB	Zambia	Lusaka	Africa	20017675	18927715	16248230	137
233	74	ZWE	Zimbabwe	Harare	Africa	16320537	15669666	14154937	128

234 rows × 17 columns

In [3]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 234 entries, 0 to 233
Data columns (total 17 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   Rank                         234 non-null    int64  
 1   CCA3                         234 non-null    object 
 2   Country/Territory            234 non-null    object 
 3   Capital                      234 non-null    object 
 4   Continent                    234 non-null    object 
 5   2022 Population              234 non-null    int64  
 6   2020 Population              234 non-null    int64  
 7   2015 Population              234 non-null    int64  
 8   2010 Population              234 non-null    int64  
 9   2000 Population              234 non-null    int64  
 10  1990 Population              234 non-null    int64  
 11  1980 Population              234 non-null    int64  
 12  1970 Population              234 non-null    int64  
 13  Area (km²)                   234 non-null    int64  
 14  Density (per km²)            234 non-null    float64
 15  Growth Rate                  234 non-null    float64
 16  World Population Percentage  234 non-null    float64
dtypes: float64(3), int64(10), object(4)
memory usage: 31.2+ KB
```

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

Out[4]:

	Rank	CCA3	Country/Territory	Capital	Continent	2022 Population	2020 Population	2015 Population	2 Popula
0	36	AFG	Afghanistan	Kabul	Asia	41128771	38972230	33753499	2818
1	138	ALB	Albania	Tirana	Europe	2842321	2866849	2882481	291
2	34	DZA	Algeria	Algiers	Africa	44903225	43451666	39543154	3585
3	213	ASM	American Samoa	Pago Pago	Oceania	44273	46189	51368	54
4	203	AND	Andorra	Andorra la Vella	Europe	79824	77700	71746	7

In [5]:
```
features=df.iloc[:,:-1]
target=df.iloc[:,-1]
```

In [6]:
```
features
```

Out[6]:

	Rank	CCA3	Country/Territory	Capital	Continent	2022 Population	2020 Population	2015 Population	Popu
0	36	AFG	Afghanistan	Kabul	Asia	41128771	38972230	33753499	28
1	138	ALB	Albania	Tirana	Europe	2842321	2866849	2882481	2
2	34	DZA	Algeria	Algiers	Africa	44903225	43451666	39543154	35
3	213	ASM	American Samoa	Pago Pago	Oceania	44273	46189	51368	
4	203	AND	Andorra	Andorra la Vella	Europe	79824	77700	71746	
...	...	...	...	...	...	...	...	...	
229	226	WLF	Wallis and Futuna	Mata-Utu	Oceania	11572	11655	12182	
230	172	ESH	Western Sahara	El Aaiún	Africa	575986	556048	491824	
231	46	YEM	Yemen	Sanaa	Asia	33696614	32284046	28516545	24
232	63	ZMB	Zambia	Lusaka	Africa	20017675	18927715	16248230	13
233	74	ZWE	Zimbabwe	Harare	Africa	16320537	15669666	14154937	12

234 rows × 16 columns

In [7]:
```
target
```

Out[7]:
```
0      0.52
1      0.04
2      0.56
3      0.00
4      0.00
       ...
229    0.00
230    0.01
231    0.42
232    0.25
233    0.20
Name: World Population Percentage, Length: 234, dtype: float64
```

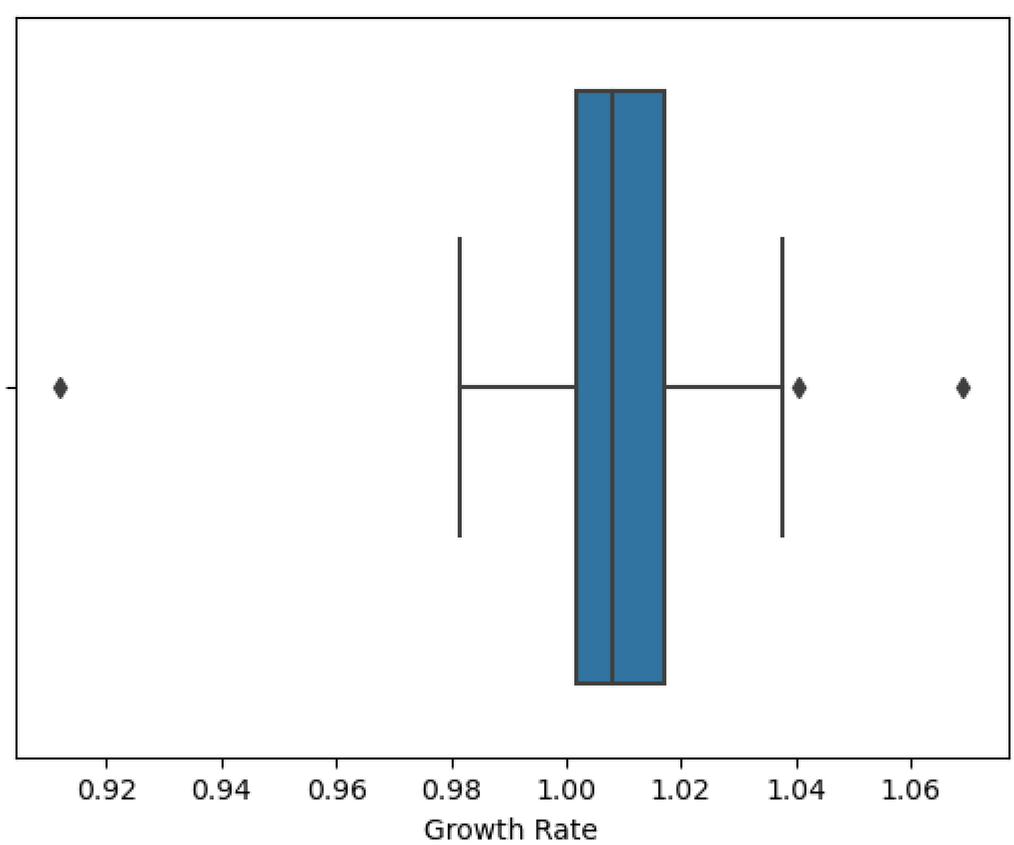
In [8]:
```
features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 234 entries, 0 to 233
Data columns (total 16 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Rank               234 non-null    int64  
 1   CCA3               234 non-null    object 
 2   Country/Territory  234 non-null    object 
 3   Capital            234 non-null    object 
 4   Continent          234 non-null    object 
 5   2022 Population    234 non-null    int64  
 6   2020 Population    234 non-null    int64  
 7   2015 Population    234 non-null    int64  
 8   2010 Population    234 non-null    int64  
 9   2000 Population    234 non-null    int64  
 10  1990 Population    234 non-null    int64  
 11  1980 Population    234 non-null    int64  
 12  1970 Population    234 non-null    int64  
 13  Area (km²)         234 non-null    int64  
 14  Density (per km²)  234 non-null    float64
 15  Growth Rate        234 non-null    float64
dtypes: float64(2), int64(10), object(4)
memory usage: 29.4+ KB
```

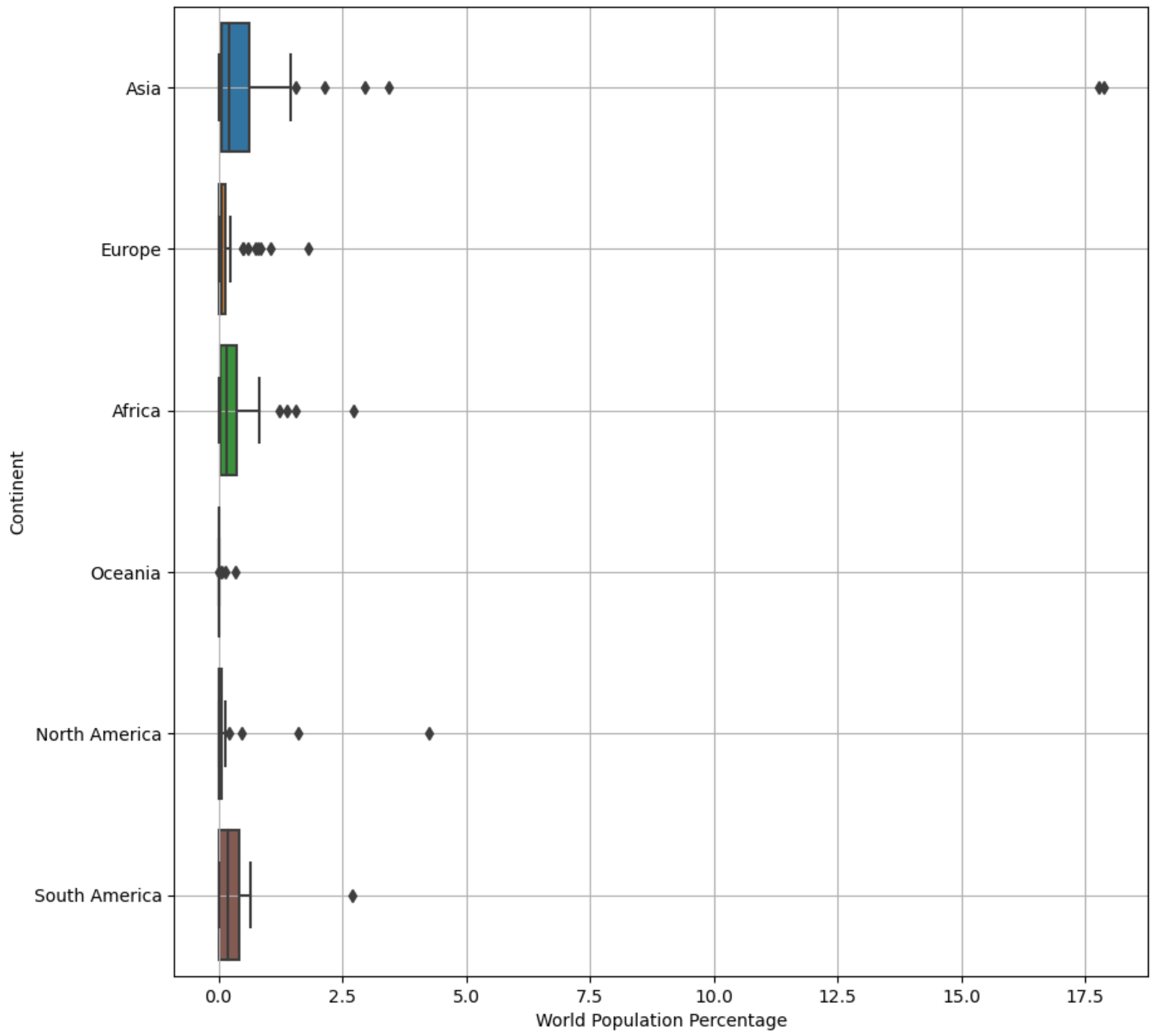
Outlier

In [9]:
```
sns.boxplot(data=df,x="Growth Rate")
```

Out[9]: <Axes: xlabel='Growth Rate'>



In [10]:
```
plt.figure(figsize=(10,10))
sns.boxplot(data=features,x=target,y="Continent")
plt.grid()
```



In [11]:
```
features[(features.Continent=="South America")&(target>2.6)]
```

Out[11]:

	Rank	CCA3	Country/Territory	Capital	Continent	2022 Population	2020 Population	2015 Population	Popul
27	7	BRA	Brazil	Brasilia	South America	215313498	213196304	205188205	19635

In [12]:
```
target.drop(27,axis=0,inplace=True)
```

In [13]:
```
features
```

Out[13]:

	Rank	CCA3	Country/Territory	Capital	Continent	2022 Population	2020 Population	2015 Population	Popu
0	36	AFG	Afghanistan	Kabul	Asia	41128771	38972230	33753499	281
1	138	ALB	Albania	Tirana	Europe	2842321	2866849	2882481	29
2	34	DZA	Algeria	Algiers	Africa	44903225	43451666	39543154	358
3	213	ASM	American Samoa	Pago Pago	Oceania	44273	46189	51368	
4	203	AND	Andorra	Andorra la Vella	Europe	79824	77700	71746	
...	...	...	...	...	...	...	...	...	
229	226	WLF	Wallis and Futuna	Mata-Utu	Oceania	11572	11655	12182	
230	172	ESH	Western Sahara	El Aaiún	Africa	575986	556048	491824	4
231	46	YEM	Yemen	Sanaa	Asia	33696614	32284046	28516545	247
232	63	ZMB	Zambia	Lusaka	Africa	20017675	18927715	16248230	137
233	74	ZWE	Zimbabwe	Harare	Africa	16320537	15669666	14154937	128

234 rows × 16 columns

In [14]:
```
target
```

Out[14]:
```
0      0.52
1      0.04
2      0.56
3      0.00
4      0.00
       ...
229    0.00
230    0.01
231    0.42
232    0.25
233    0.20
Name: World Population Percentage, Length: 233, dtype: float64
```

In [15]:
```
features[(features.Continent=="Oceania")&(target>0.0)]
```

Out[15]:

	Rank	CCA3	Country/Territory	Capital	Continent	2022 Population	2020 Population	2015 Population	Po
11	55	AUS	Australia	Canberra	Oceania	26177413	25670051	23820236	2
66	162	FJI	Fiji	Suva	Oceania	929766	920422	917200	
146	123	NZL	New Zealand	Wellington	Oceania	5185288	5061133	4590590	
160	93	PNG	Papua New Guinea	Port Moresby	Oceania	10142619	9749640	8682174	
191	166	SLB	Solomon Islands	Honiara	Oceania	724273	691191	612660	

In [16]:
```
features.drop([11,66,146,160,191],axis=0,inplace=True)
target.drop([11,66,146,160,191],axis=0,inplace=True)
```

In [17]:
```
features[(features.Continent=="Africa")&(target>0.6)]
```

Out[17]:

	Rank	CCA3	Country/Territory	Capital	Continent	2022 Population	2020 Population	2015 Population	Pop
55	15	COD	DR Congo	Kinshasa	Africa	99010212	92853164	78656904	66
57	14	EGY	Egypt	Cairo	Africa	110990103	107465134	97723799	87
63	12	ETH	Ethiopia	Addis Ababa	Africa	123379924	117190911	102471895	89
106	27	KEN	Kenya	Nairobi	Africa	54027487	51985780	46851488	4
149	6	NGA	Nigeria	Abuja	Africa	218541212	208327405	183995785	160
193	24	ZAF	South Africa	Pretoria	Africa	59893885	58801927	55876504	5
205	22	TZA	Tanzania	Dodoma	Africa	65497748	61704518	52542823	45

In [18]:
```
features.drop([55,57,63,106,149,193,205],axis=0,inplace=True)
target.drop([55,57,63,106,149,193,205],axis=0,inplace=True)
```

In [19]:
```
features[(features.Continent=="Europe")&(target>0.1)]
```

Out[19]:

	Rank	CCA3	Country/Territory	Capital	Continent	2022 Population	2020 Population	2015 Population	P
12	99	AUT	Austria	Vienna	Europe	8939617	8907777	8642421	
18	96	BLR	Belarus	Minsk	Europe	9534954	9633740	9700609	
19	81	BEL	Belgium	Brussels	Europe	11655930	11561717	11248303	
50	88	CZE	Czech Republic	Prague	Europe	10493986	10530953	10523798	
68	23	FRA	France	Paris	Europe	64626628	64480053	63809769	
74	19	DEU	Germany	Berlin	Europe	83369843	83328988	82073226	
77	90	GRC	Greece	Athens	Europe	10384971	10512232	10806641	
90	94	HUN	Hungary	Budapest	Europe	9967308	9750573	9844246	
99	25	ITA	Italy	Rome	Europe	59037474	59500579	60232906	
144	71	NLD	Netherlands	Amsterdam	Europe	17564014	17434557	17041107	
164	37	POL	Poland	Warsaw	Europe	39857145	38428366	38553146	
165	92	PRT	Portugal	Lisbon	Europe	10270865	10298192	10365435	
170	64	ROU	Romania	Bucharest	Europe	19659267	19442038	19906079	
171	9	RUS	Russia	Moscow	Europe	144713314	145617329	144668389	1
196	30	ESP	Spain	Madrid	Europe	47558630	47363807	46431342	
200	87	SWE	Sweden	Stockholm	Europe	10549347	10368969	9849349	
201	101	CHE	Switzerland	Bern	Europe	8740472	8638613	8281732	
218	38	UKR	Ukraine	Kiev	Europe	39701739	43909666	44982564	
220	21	GBR	United Kingdom	London	Europe	67508936	67059474	65224364	

In [20]:
```
features.drop([12,18,19,50,68,74,77,90,99,144,164,165,170,171,196,200,201,
target.drop([12,18,19,50,68,74,77,90,99,144,164,165,170,171,196,200,201,21
```

In [21]:

```
features[(features.Continent=="Asia")&(target>0.5)]
```

Out[21]:

	Rank	CCA3	Country/Territory	Capital	Continent	2022 Population	2020 Population	2015 Population
0	36	AFG	Afghanistan	Kabul	Asia	41128771	38972230	33753499
16	8	BGD	Bangladesh	Dhaka	Asia	171186372	167420951	157830000
41	1	CHN	China	Beijing	Asia	1425887337	1424929781	1393715448
92	2	IND	India	New Delhi	Asia	1417173173	1396387127	1322866505
93	4	IDN	Indonesia	Jakarta	Asia	275501339	271857970	259091970
94	17	IRN	Iran	Tehran	Asia	88550570	87290193	81790841
95	35	IRQ	Iraq	Baghdad	Asia	44496122	42556984	37757813
102	11	JPN	Japan	Tokyo	Asia	123951692	125244761	127250933
140	26	MMR	Myanmar	Nay Pyi Taw	Asia	54179306	53423198	51483949
156	5	PAK	Pakistan	Islamabad	Asia	235824862	227196741	210969298
163	13	PHL	Philippines	Manila	Asia	115559009	112190977	103031365
194	29	KOR	South Korea	Seoul	Asia	51815810	51844690	50994401
206	20	THA	Thailand	Bangkok	Asia	71697030	71475664	70294397
213	18	TUR	Turkey	Ankara	Asia	85341241	84135428	79646178
228	16	VNM	Vietnam	Hanoi	Asia	98186856	96648685	92191398

In [22]:

```
features.drop([0,16,41,92,93,94,95,102,140,156,163,194,206,213,228],axis=0
target.drop([0,16,41,92,93,94,95,102,140,156,163,194,206,213,228],axis=0,i
```

In [23]:

```
features[(features.Continent=="North America")&(target>0.1)]
```

Out[23]:

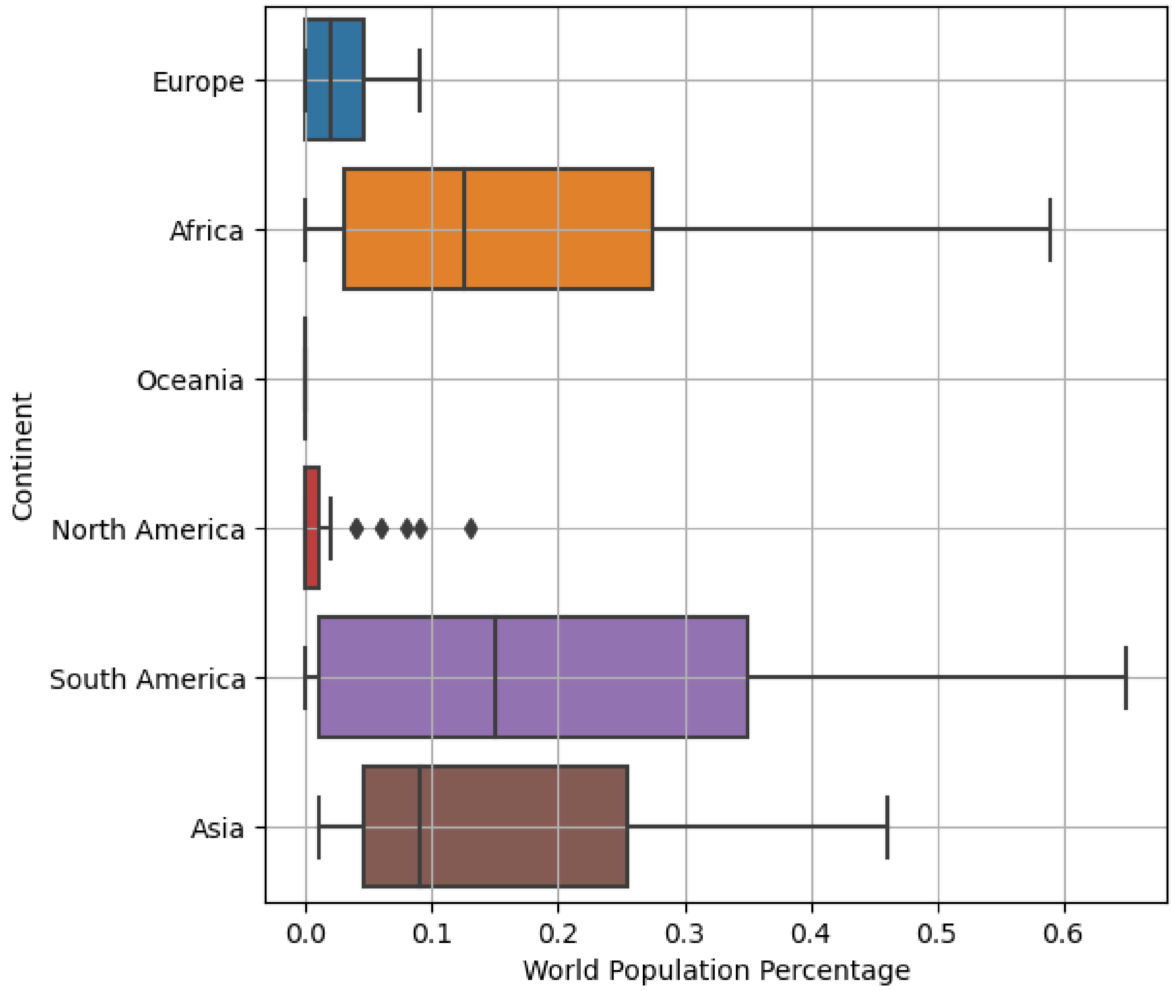
	Rank	CCA3	Country/Territory	Capital	Continent	2022 Population	2020 Population	2015 Population
35	39	CAN	Canada	Ottawa	North America	38454327	37888705	35732126
47	85	CUB	Cuba	Havana	North America	11212191	11300698	11339894
54	84	DOM	Dominican Republic	Santo Domingo	North America	11228821	10999664	10405832
82	68	GTM	Guatemala	Guatemala City	North America	17843908	17362718	16001107
87	82	HTI	Haiti	Port-au-Prince	North America	11584996	11306801	10563757
88	89	HND	Honduras	Tegucigalpa	North America	10432860	10121763	9294505
131	10	MEX	Mexico	Mexico City	North America	127504125	125998302	120149897
221	3	USA	United States	Washington, D.C.	North America	338289857	335942003	324607776

In [24]:

```
features.drop([35,47,54,82,87,131,221],axis=0,inplace=True)
target.drop([35,47,54,82,87,131,221],axis=0,inplace=True)
```

In [25]:

```python
plt.figure(figsize=(6,6))
sns.boxplot(data=features,x=target,y="Continent")
plt.grid()
```



Skewness Removal

In [26]:

```python
features
```

Out[26]:

	Rank	CCA3	Country/Territory	Capital	Continent	2022 Population	2020 Population	2015 Population	Popu
1	138	ALB	Albania	Tirana	Europe	2842321	2866849	2882481	29
2	34	DZA	Algeria	Algiers	Africa	44903225	43451666	39543154	358
3	213	ASM	American Samoa	Pago Pago	Oceania	44273	46189	51368	
4	203	AND	Andorra	Andorra la Vella	Europe	79824	77700	71746	
5	42	AGO	Angola	Luanda	Africa	35588987	33428485	28127721	233
...	...	...	...	...	...	...	...	...	
229	226	WLF	Wallis and Futuna	Mata-Utu	Oceania	11572	11655	12182	
230	172	ESH	Western Sahara	El Aaiún	Africa	575986	556048	491824	4
231	46	YEM	Yemen	Sanaa	Asia	33696614	32284046	28516545	247
232	63	ZMB	Zambia	Lusaka	Africa	20017675	18927715	16248230	137
233	74	ZWE	Zimbabwe	Harare	Africa	16320537	15669666	14154937	128

181 rows × 16 columns

In [27]:
```python
features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 181 entries, 1 to 233
Data columns (total 16 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   Rank                 181 non-null    int64  
 1   CCA3                 181 non-null    object 
 2   Country/Territory    181 non-null    object 
 3   Capital              181 non-null    object 
 4   Continent            181 non-null    object 
 5   2022 Population      181 non-null    int64  
 6   2020 Population      181 non-null    int64  
 7   2015 Population      181 non-null    int64  
 8   2010 Population      181 non-null    int64  
 9   2000 Population      181 non-null    int64  
 10  1990 Population      181 non-null    int64  
 11  1980 Population      181 non-null    int64  
 12  1970 Population      181 non-null    int64  
 13  Area (km²)           181 non-null    int64  
 14  Density (per km²)    181 non-null    float64
 15  Growth Rate          181 non-null    float64
dtypes: float64(2), int64(10), object(4)
memory usage: 28.1+ KB
```

In [28]:
```python
features.select_dtypes(["int64","float64"])
```

Out[28]:

	Rank	2022 Population	2020 Population	2015 Population	2010 Population	2000 Population	1990 Population	1980 Population
1	138	2842321	2866849	2882481	2913399	3182021	3295066	2941651
2	34	44903225	43451666	39543154	35856344	30774621	25518074	18739378
3	213	44273	46189	51368	54849	58230	47818	32886
4	203	79824	77700	71746	71519	66097	53569	35611
5	42	35588987	33428485	28127721	23364185	16394062	11828638	8330047
...	...	...	...	...	...	...	...	...
229	226	11572	11655	12182	13142	14723	13454	11315
230	172	575986	556048	491824	413296	270375	178529	116775
231	46	33696614	32284046	28516545	24743946	18628700	13375121	9204938
232	63	20017675	18927715	16248230	13792086	9891136	7686401	5720438
233	74	16320537	15669666	14154937	12839771	11834676	10113893	7049926

181 rows × 12 columns

In [29]:
```python
colname=features.select_dtypes(["int64","float64"]).columns
```

In [30]:
```python
colname
```

Out[30]:
```
Index(['Rank', '2022 Population', '2020 Population', '2015 Population',
       '2010 Population', '2000 Population', '1990 Population',
       '1980 Population', '1970 Population', 'Area (km²)', 'Density (per km
²)',
       'Growth Rate'],
      dtype='object')
```

In [31]:
```python
from scipy.stats import skew
```

In [32]:
```python
skew(features["2022 Population"])
```

Out[32]:
```
7.037204364085802
```

In [33]:
```
features[colname]
```

Out[33]:

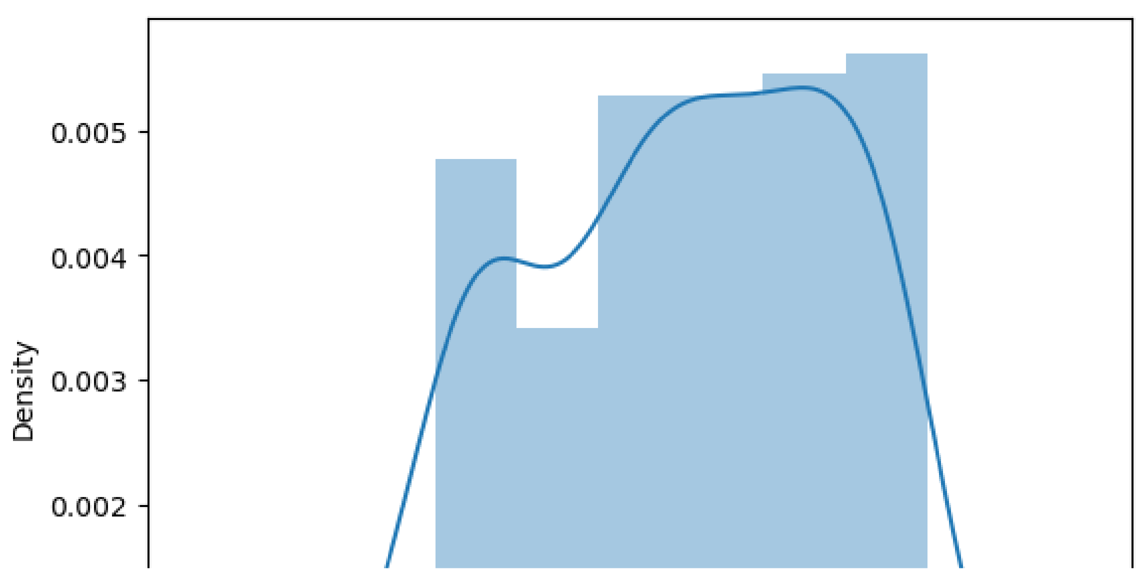
	Rank	2022 Population	2020 Population	2015 Population	2010 Population	2000 Population	1990 Population	1980 Population	P
1	138	2842321	2866849	2882481	2913399	3182021	3295066	2941651	
2	34	44903225	43451666	39543154	35856344	30774621	25518074	18739378	
3	213	44273	46189	51368	54849	58230	47818	32886	
4	203	79824	77700	71746	71519	66097	53569	35611	
5	42	35588987	33428485	28127721	23364185	16394062	11828638	8330047	
...	...	...	...	...	...	...	...	...	
229	226	11572	11655	12182	13142	14723	13454	11315	
230	172	575986	556048	491824	413296	270375	178529	116775	
231	46	33696614	32284046	28516545	24743946	18628700	13375121	9204938	
232	63	20017675	18927715	16248230	13792086	9891136	7686401	5720438	
233	74	16320537	15669666	14154937	12839771	11834676	10113893	7049926	

181 rows × 12 columns

In [34]:
```
for col in features[colname]:
    print(col)
    print(skew(features[col]))

    plt.figure()
    sns.distplot(features[col])
    plt.show()
```

```
Rank
-0.19185958806082648
```



In [35]:
```python
pd.concat([features,target],axis=1).corr()
```

Out[35]:

	Rank	2022 Population	2020 Population	2015 Population	2010 Population	2000 Population	1990 Population	Po
Rank	1.000000	-0.640997	-0.633836	-0.617627	-0.602510	-0.573570	-0.556838	-
2022 Population	-0.640997	1.000000	0.999805	0.997740	0.994449	0.985734	0.976428	
2020 Population	-0.633836	0.999805	1.000000	0.998826	0.996146	0.988542	0.979991	
2015 Population	-0.617627	0.997740	0.998826	1.000000	0.998978	0.994023	0.987278	
2010 Population	-0.602510	0.994449	0.996146	0.998978	1.000000	0.997317	0.992098	
2000 Population	-0.573570	0.985734	0.988542	0.994023	0.997317	1.000000	0.998226	
1990 Population	-0.556838	0.976428	0.979991	0.987278	0.992098	0.998226	1.000000	
1980 Population	-0.544524	0.967499	0.971535	0.980043	0.985946	0.994579	0.998658	
1970 Population	-0.538435	0.957749	0.962178	0.971731	0.978524	0.989339	0.995326	
Area (km²)	-0.447583	0.845027	0.847612	0.850730	0.850739	0.850533	0.852542	
Density (per km²)	0.116835	-0.075786	-0.074620	-0.072122	-0.070078	-0.066461	-0.065487	-
Growth Rate	-0.432773	0.200754	0.189180	0.164294	0.147622	0.110363	0.084442	
World Population Percentage	-0.852979	0.999825	0.999531	0.995797	0.989211	0.969479	0.944414	

In [36]:
```python
pd.concat([features,target],axis=1).corr().style.background_gradient()
```

Out[36]:

	Rank	2022 Population	2020 Population	2015 Population	2010 Population	2000 Population	1990 Population	Po
Rank	1.000000	-0.640997	-0.633836	-0.617627	-0.602510	-0.573570	-0.556838	-
2022 Population	-0.640997	1.000000	0.999805	0.997740	0.994449	0.985734	0.976428	
2020 Population	-0.633836	0.999805	1.000000	0.998826	0.996146	0.988542	0.979991	
2015 Population	-0.617627	0.997740	0.998826	1.000000	0.998978	0.994023	0.987278	
2010 Population	-0.602510	0.994449	0.996146	0.998978	1.000000	0.997317	0.992098	
2000 Population	-0.573570	0.985734	0.988542	0.994023	0.997317	1.000000	0.998226	
1990 Population	-0.556838	0.976428	0.979991	0.987278	0.992098	0.998226	1.000000	
1980 Population	-0.544524	0.967499	0.971535	0.980043	0.985946	0.994579	0.998658	
1970 Population	-0.538435	0.957749	0.962178	0.971731	0.978524	0.989339	0.995326	
Area (km²)	-0.447583	0.845027	0.847612	0.850730	0.850739	0.850533	0.852542	
Density (per km²)	0.116835	-0.075786	-0.074620	-0.072122	-0.070078	-0.066461	-0.065487	-
Growth Rate	-0.432773	0.200754	0.189180	0.164294	0.147622	0.110363	0.084442	
World Population Percentage	-0.852979	0.999825	0.999531	0.995797	0.989211	0.969479	0.944414	

In [37]:
```
1 pd.concat([features,target],axis=1).corr()["Growth Rate"].sort_values()
```

Out[37]:
```
Rank                            -0.432773
Density (per km²)               -0.095177
1970 Population                  0.047967
1980 Population                  0.064225
1990 Population                  0.084442
2000 Population                  0.110363
Area (km²)                       0.134405
2010 Population                  0.147622
2015 Population                  0.164294
2020 Population                  0.189180
2022 Population                  0.200754
World Population Percentage      0.375083
Growth Rate                      1.000000
Name: Growth Rate, dtype: float64
```

In [38]:
```
1 np.log(-1)
```

Out[38]:
```
nan
```

In [39]:
```
1 np.sqrt(-1)
```

Out[39]:
```
nan
```

In [40]:
```
1 n=25
2 print(np.log(n))
3 print(np.sqrt(n))
```

```
3.2188758248682006
5.0
```

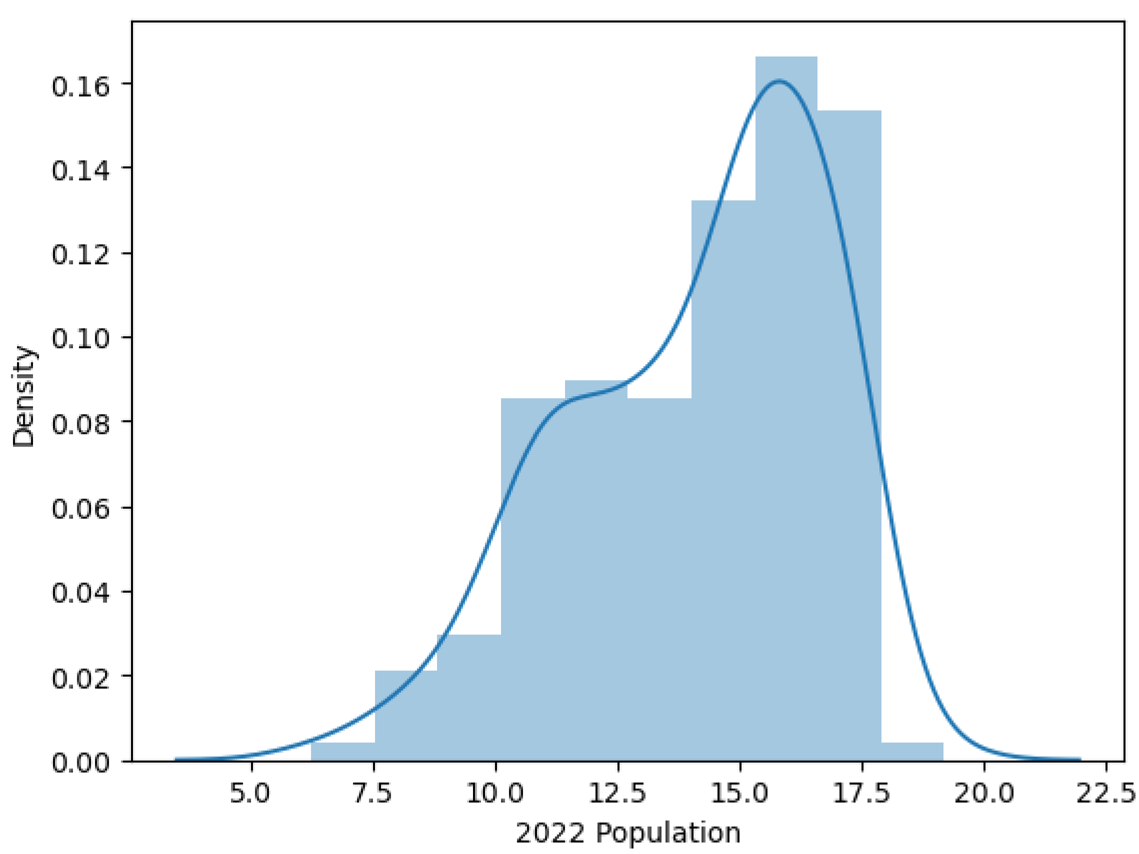
In [41]:
```
1 features["2022 Population"]=np.log(features["2022 Population"])
```

In [42]:
```
1 skew(features["2022 Population"])
```

Out[42]:
```
-0.6168718222437785
```

In [45]:
```
1 sns.distplot(features["2022 Population"])
```

Out[45]:
```
<Axes: xlabel='2022 Population', ylabel='Density'>
```



In [44]:

```
pd.concat([features,target],axis=1).corr().style.background_gradient()
```

Out[44]:

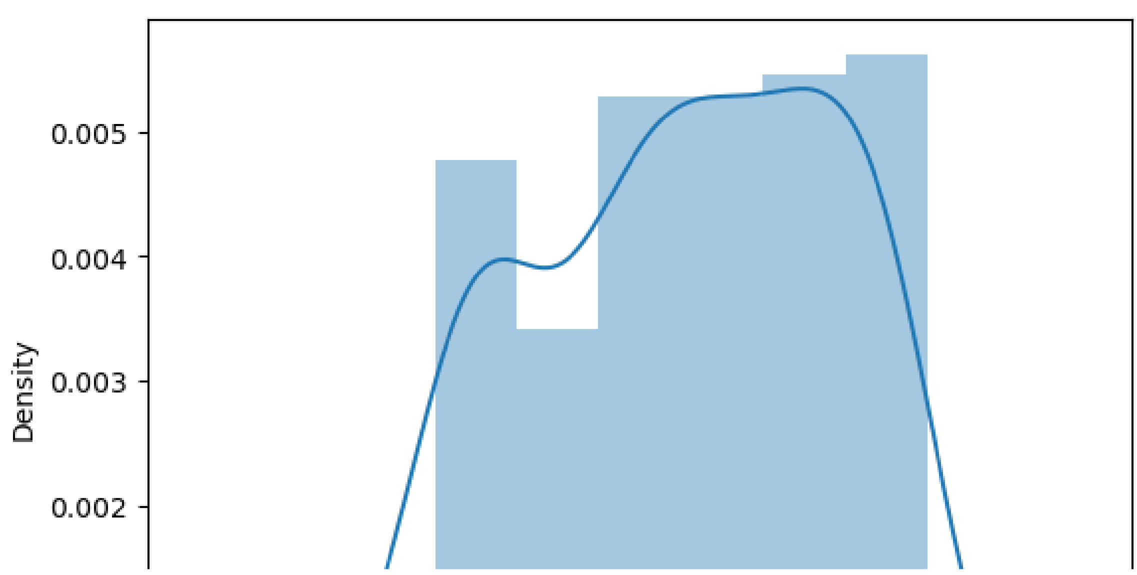
	Rank	2022 Population	2020 Population	2015 Population	2010 Population	2000 Population	1990 Population
Rank	1.000000	-0.960216	-0.633836	-0.617627	-0.602510	-0.573570	-0.556838
2022 Population	-0.960216	1.000000	0.537661	0.525172	0.513030	0.490073	0.478196
2020 Population	-0.633836	0.537661	1.000000	0.998826	0.996146	0.988542	0.979991
2015 Population	-0.617627	0.525172	0.998826	1.000000	0.998978	0.994023	0.987278
2010 Population	-0.602510	0.513030	0.996146	0.998978	1.000000	0.997317	0.992098
2000 Population	-0.573570	0.490073	0.988542	0.994023	0.997317	1.000000	0.998226
1990 Population	-0.556838	0.478196	0.979991	0.987278	0.992098	0.998226	1.000000
1980 Population	-0.544524	0.469816	0.971535	0.980043	0.985946	0.994579	0.998658
1970 Population	-0.538435	0.466774	0.962178	0.971731	0.978524	0.989339	0.995326
Area (km²)	-0.447583	0.385148	0.847612	0.850730	0.850739	0.850533	0.852542
Density (per km²)	0.116835	-0.102247	-0.074620	-0.072122	-0.070078	-0.066461	-0.065487
Growth Rate	-0.432773	0.409971	0.189180	0.164294	0.147622	0.110363	0.084442
World Population Percentage	-0.852979	0.713287	0.999531	0.995797	0.989211	0.969479	0.944414

In [46]:

```
for col in features[colname]:
    print(col)
    print(skew(features[col]))

    plt.figure()
    sns.distplot(features[col])
    plt.show()
```

```
Rank
-0.19185958806082648
```



In [47]:

```
features
```

Out[47]:

	Rank	CCA3	Country/Territory	Capital	Continent	2022 Population	2020 Population	2015 Population	Popu
1	138	ALB	Albania	Tirana	Europe	14.860132	2866849	2882481	29
2	34	DZA	Algeria	Algiers	Africa	17.620020	43451666	39543154	358
3	213	ASM	American Samoa	Pago Pago	Oceania	10.698130	46189	51368	
4	203	AND	Andorra	Andorra la Vella	Europe	11.287579	77700	71746	
5	42	AGO	Angola	Luanda	Africa	17.387547	33428485	28127721	233
...	...	...	...	...	...	...	...	...	
229	226	WLF	Wallis and Futuna	Mata-Utu	Oceania	9.356344	11655	12182	
230	172	ESH	Western Sahara	El Aaiún	Africa	13.263839	556048	491824	4
231	46	YEM	Yemen	Sanaa	Asia	17.332908	32284046	28516545	247
232	63	ZMB	Zambia	Lusaka	Africa	16.812126	18927715	16248230	137
233	74	ZWE	Zimbabwe	Harare	Africa	16.607935	15669666	14154937	128

181 rows × 16 columns

In [ ]:

```

```