In [1]:

```
import pandas as pd
import sklearn
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:

```
data = pd.read_csv("C:\\Users\\prady\\OneDrive\\Desktop\\african_crises.csv") # importing data
```

In [3]:

```
data.head()
```

Out[3]:

	case	cc3	country	year	systemic_crisis	exch_usd	domestic_debt_in_default	sovereign_external_debt_default	gdp_weighted_defa
0	1	DZA	Algeria	1870	1	0.052264	0	0	
1	1	DZA	Algeria	1871	0	0.052798	0	0	
2	1	DZA	Algeria	1872	0	0.052274	0	0	
3	1	DZA	Algeria	1873	0	0.051680	0	0	
4	1	DZA	Algeria	1874	0	0.051308	0	0	

In [4]:

```
from sklearn.preprocessing import LabelEncoder
labelencoder = LabelEncoder()
```

In [5]:

```
# Doing label encoding to the banking_crisis feature as it is a categorical variable

data['banking_crisis'] = labelencoder.fit_transform(data['banking_crisis'])
```

In [6]:

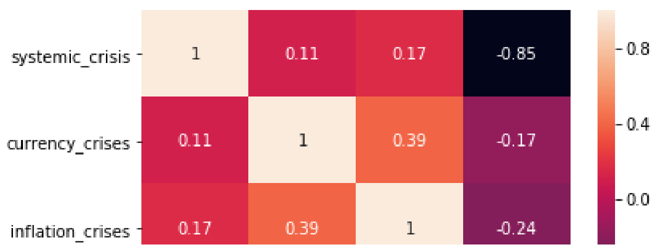
```
corrdata = data[['systemic_crisis','currency_crises','inflation_crises','banking_crisis']]
```

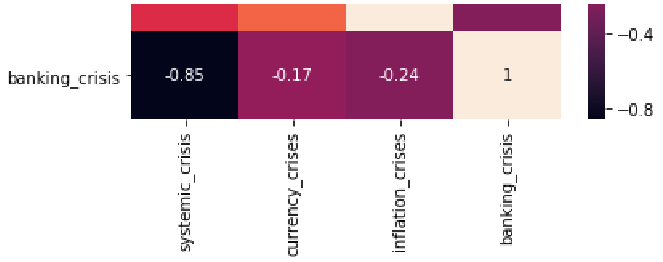
In [7]:

```
## 1. Are there any correlations among systemic_crisis, currency_crises, inflation_crises and bank
ing_crisis ?
sns.heatmap(corrdata.corr(),annot=True)
# This heatmap gives us the correlations between the required data.

# Alternatively we could also directly calculate the correlations between the data using point bis
erial correlation
# present in scipy.stats library
```

Out[7]:

<matplotlib.axes._subplots.AxesSubplot at 0x2a8e4d72f28>





In [8]:

```
# from the correlation plot we could see that there is a strong negative correlation of 0.85 betwe
en systemic_crisis
# and banking_crisis.

# There is a slight positive correlation of 0.39 between currency_crises and inflation_crises

# There is not much correlations between the remaining variable pairs and the correlations could b
e viewed from the heatmap.
```

In [ ]:

```

```

In [9]:

```
## 2. Is there any relation between yearly change in exch_usd and inflation_annual_cpi?
```

In [10]:

```
required = data[['exch_usd','inflation_annual_cpi']]
required.corr(method='pearson')
```

Out[10]:

	exch_usd	inflation_annual_cpi
exch_usd	1.000000	-0.011947
inflation_annual_cpi	-0.011947	1.000000

In [11]:

```
# exch_usd and inflation_annual_cpi has a negative correlation of -0.011947.
```

In [ ]:

```

```

In [12]:

```
## 3. Which country has most stable exchange rate over the years?

stabledata = data[['country','year','exch_usd','inflation_annual_cpi']]
```

In [13]:

```
stabledata.groupby(['country']).exch_usd.var()
```

Out[13]:

```
country
Algeria                      865.158479
Angola                      1049.574251
Central African Republic   21821.299240
Egypt                          2.978427
Ivory Coast                34563.267148
```

```
Kenya                          934.769285
Mauritius                      103.467011
Morocco                          8.535214
Nigeria                       3490.149060
South Africa                     7.187258
Tunisia                      12208.309916
Zambia                           3.674024
Zimbabwe                      7023.383637
Name: exch_usd, dtype: float64
```

In [14]:

```
# By observing the variances we could observe that Egypt has least variance depicting more stabili
ty.

# Therefore, Ivory coast has more stable exch_usd (exchange rate) over the years.
```

In [ ]:

In [15]:

```
## 4. Which country has most stable inflation_annual_cpi over the years?

stabledata.groupby(['country']).inflation_annual_cpi.var()
```

Out[15]:

```
country
Algeria                     2.061941e+02
Angola                      3.392400e+05
Central African Republic    4.887568e+01
Egypt                       9.614490e+01
Ivory Coast                 4.355069e+01
Kenya                       6.097410e+01
Mauritius                   5.814585e+01
Morocco                     1.499700e+02
Nigeria                     2.450365e+02
South Africa                4.377161e+01
Tunisia                     2.168103e+02
Zambia                      1.247473e+03
Zimbabwe                    5.372407e+12
Name: inflation_annual_cpi, dtype: float64
```

In [16]:

```
# By observing the variances we could observe that Ivory Coast has least variance depicting more s
tability.

# Therefore, Ivory coast has more stable inflation_annual_cpi over the years.
```

In [ ]:

In [17]:

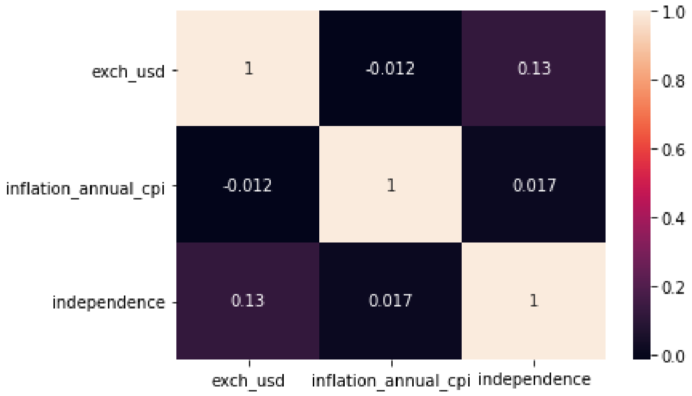
```
## 5. Does gaining independence has any effects on exch_usd and inflation_annual_cpi ?

required = data[['exch_usd','inflation_annual_cpi','independence']]
```

In [18]:

```
sns.heatmap(required.corr(),annot=True)
```

Out[18]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2a8e510f748>
```



In [19]:

```
# Independence has a minor effect with a correlation of 0.13 on exch_usd and much negligible effec
t
# on inflation_annual_cpi with a correlation of 0.017.

# So, gaining independence has very less effect on exch_usd and inflation_annual_cpi.
```

In [ ]:

```

```