RM_A02_Group_E

November 8, 2022

1 Research Methods UHH - Knowledge Technology Research Group - WiSe 2022/2023

1.1 Assignment #2 - Empirical Studies & EDA

1.1.1 Group: E

1.1.2 Names of members: Parvin Abbasi, Aron Jinga, Atharva Phatak

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1.1.3 Instructions:

Please answer the questions below. Copy this notebook and enter your answers underneath each task description, inserting cells as needed. You may use a combination of python 3, markdown, and LaTex to formulate your responses. In order to successfully complete the assignment, you will need the lecture material provided in the RM moodle course, especially L02 & L03.

Make sure to use only a copy of this notebook for your answers instead of a new/blank notebook.

1.1.4 Grading Criteria:

In order to successfully pass this assignment, you will need **at least a total of 70 points out of 100 points**, and every task has to be tackled.

1.1.5 Submission:

Please upload the following two files **until Tuesday, November 8, 2022, 20:00 CET (Germany)** together in a .zip archive in moodle: 1. a (single) copy of this jupyter notebook containing your answers for all tasks (file extension: .ipynb) 2. an exported PDF document of the jupyter notebook (file extension: .pdf)

1.1.6 Presentation:

Make sure that each (!) group member takes part in solving this assignment and is prepared to answer questions and/or present solutions from your submitted notebook during our assignment revision meeting scheduled for **Wednesday, November 16, 2022, 10:00 - 13:00 CET (Germany)**.

1.1.7 File Naming:

Add the group letter to the file name prior to submission. For example, if your group letter is "A" (see group selection in moodle), you would use the following filename: 1. RM_A02_Group_A.ipynb 2. RM_A02_Group_A.pdf

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[39]:
```
import pandas as pd
import seaborn as sbs
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams['figure.dpi'] = 100
sbs.set(rc={"figure.dpi":100, 'savefig.dpi':400})
```

[40]:
```
df = pd.read_csv(r'Datasets/CRU_data.csv')
sbs.set_theme()
months = ['JAN', 'FEB', 'MAR', 'APR', 'MAY', 'JUN', 'JUL', 'AUG', 'SEP', 'OCT',␣
↪'NOV', 'DEC']
```

Task 1 [10 points] Data Scales

1. For each of the features in the CRU dataset (e.g., precipitation), identify all scales of data whose definition is valid for all entries in the columns that belong to that feature. Create a table using python code that contains all features as rows, data scales as columns, and binary table entries indicating whether the feature values (i.e., column entries in the database) correspond to the data scale or not.
2. For each of the features, briefly explain to which of the errors mentioned in the lecture this feature is prone.

[41]:
```
#Solution 1
#task1.1:
df_scale = pd.DataFrame({'Feature':  ['Country', 'Year', 'Tempreture', 'Wet␣
↪days', 'Precipitation' ],
        'Categorical': ['1', '0', '0', '0', '0'],
        'Interval': ['0', '1', '1', '0', '0'],
        'Ratio': ['0', '0', '0', '1', '1'],
        'Ordinal': ['0', '0', '0', '0', '0']})
df_scale = df_scale.set_index('Feature')
df_scale
```

[41]:

	Categorical	Interval	Ratio	Ordinal
Feature				
Country	1	0	0	0
Year	0	1	0	0
Tempreture	0	1	0	0

```
Wet days                 0          0      1        0
Precipitation            0          0      1        0
```

1.1.8 1.2 :

- Measurement error can happen for temperature and wet days and precipitation because broken equipment can record wrong values.
- Sampling error can happen for temperature and wet days and precipitation because gathering data from different cities will obtain different results.
  - For example, in 2020, only Berlin and Hamburg and Stuttgart are recorded but in 1996, other three cities.
- For country and year no error is prone.

Task 2 [10 points] Types of Experiments Different types of studies and experiments were discussed in the lecture. With respect to climate data, state whether it is possible to conduct the following experiments given below. Briefly explain your reasoning and give an example for each of the four types.

1. Exploratory study
2. Assessment study
3. Observation experiments
4. Manipulation experiments

1. **Exploratory study**: By looking at data we can see that the temperature is increasing in the long term and the weather pattern is visible. Also some countries are colder than the others depending on their location. Countries that are located around the equator experience hot weather throughout the year. It is because the sun remains almost directly overhead everyday. Countries that are further North or South of the equator experience a change in seasons, when hot weather follows cold weather.
2. **Assessment study**: In assessment study we can test data's limit. The minimum recorded value for temperature is -89.2°C (-128.6°F) but in the dataset we can see -999 which is wrong.
3. **Observation experiments**: We look at the data in the past, and try to find a pattern and test if it is still applicable in the more recent data. As we yield the hypothesis the world is getting warmer, as we saw in the data for specific countries like Belarus.
4. **Manipulation experiments**: We cannot change the temperature and precipitation and so on to manipulate data

Task 3 [40 points] Visualization Plot the four statistics given below using suitable python packages:

1. Timeline of cumulative precipitation over the course of the year 2020. *(i)* world-wide and *(ii)* per country.
2. Average precipitation per wetday per country in 2020.
3. Climate diagram based on the average data from the last decade (2011 - 2020) for one country of your choice. *Note: Include the amount of precipitation as well as min, mean, and max temperature.*

4. Frequency distribution of mean temperatures in Germany in the timespans (i) 1960-1980 and (ii) 2000-2020. *Note: Use appropriate, common bins for both diagrams.*

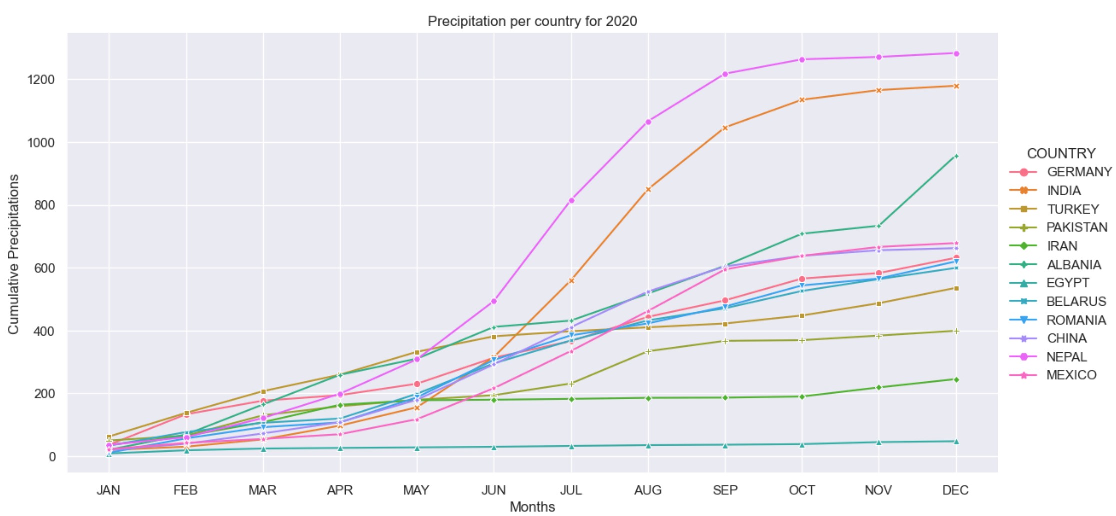
As a reminder, the following instructions will apply to **all visualization tasks** as part of the RM course: Make sure to use appropriate plot types for visualization (e.g., histogram, bar plot, scatter plot, line plot, . . .) and proper axis labeling/scaling. Add a legend to each plot to facilitate the viewer's understanding. Make sure to describe/interpret the outcome of your visualization.

Hint: It might be helpful to use the wide__to__long function in pandas to format the data for plotting!

[42]:
```
###########################################
#Solution 1 start
df_indexed = df[df['YEAR'] == 2020].set_index("COUNTRY")
df_a = df_indexed.iloc[:,65:77]
df_b = np.cumsum(df_a.T)
```

[43]:
```
#Plotting of the graph for task 1
g = sbs.relplot(data=df_b, kind='line', height = 6, aspect = 2, markers = True,␣
↪dashes = False )
g.set_xticklabels(months) #setting the x ticks to make them easier to read
g.set_xlabels("Months")
g.set_ylabels("Cumulative Precipitations")
g.set(title = "Precipitation per country for 2020")
```

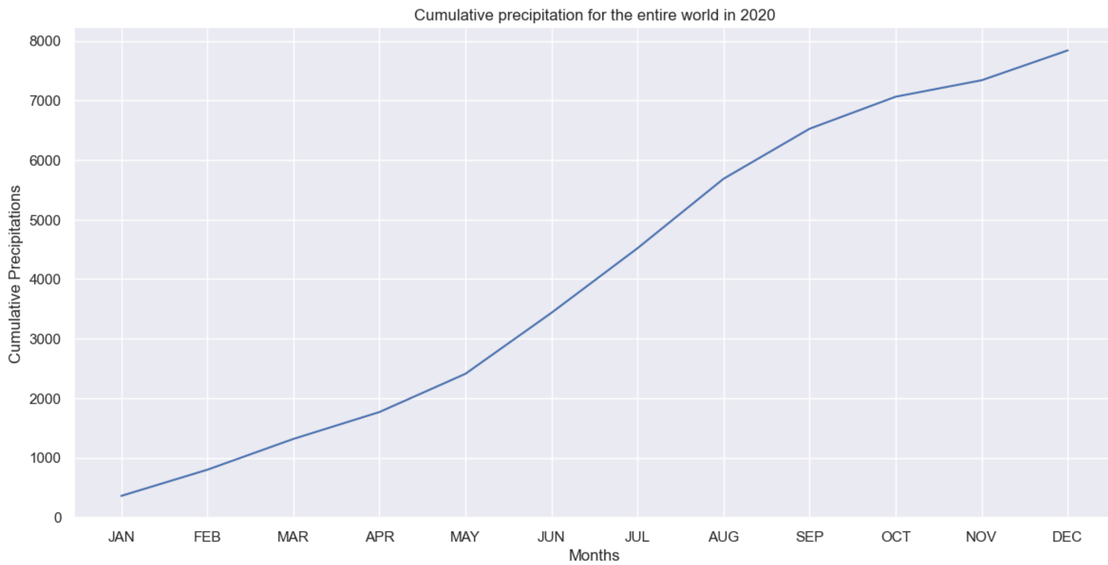
[43]: <seaborn.axisgrid.FacetGrid at 0x287d533c490>



[44]:
```
ctr_precip = sbs.relplot(data = np.cumsum(df_a.sum()),kind='line', height = 6,␣
↪aspect = 2, markers = True, dashes = False )
ctr_precip.set_xticklabels(months) #setting the x ticks to make them easier to␣
↪read
```

```
ctr_precip.set_xlabels("Months")
ctr_precip.set_ylabels("Cumulative Precipitations")
ctr_precip.set(title = "Cumulative precipitation for the entire world in 2020")
```

[44]: <seaborn.axisgrid.FacetGrid at 0x287dcd093a0>



1.1.9 3.2

[45]:
```
#### Task 2 ####
df_indexed = df[df['YEAR'] == 2020].set_index("COUNTRY")
df_precip = df_indexed.iloc[:,65:77]
df_wet = df_indexed.iloc[:,49:61]
df_wet["Total Precipitation"] = df_precip.sum(axis=1)
#For data visualization, uncomment :)
#df_wet

# We will get the average for each month by dividing the total amount of␣
↪precipitation to the wet days for each month.
for i in df_wet.columns:
    df_wet[i] = df_wet['Total Precipitation']/df_wet[i]
df_wet
```

[45]:
```
            WET_DAYS_JAN  WET_DAYS_FEB  WET_DAYS_MAR  WET_DAYS_APR  \
COUNTRY
GERMANY        48.976744     28.459459     43.875000    128.938776
INDIA         693.588235   1179.100000    535.954545    357.303030
TURKEY         55.257732     39.703704     40.606061     46.608696
PAKISTAN       95.095238    234.941176     57.057143     62.406250
```

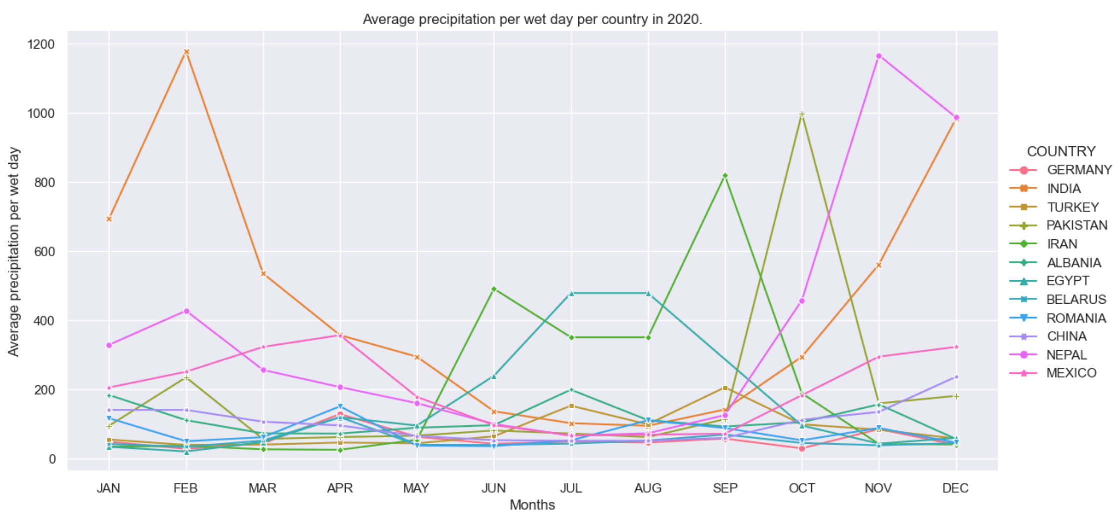
```
IRAN         34.605634    37.227273    27.000000    25.593750
ALBANIA     184.153846   111.348837    73.099237    72.545455
EGYPT        34.214286    20.826087    47.900000   119.750000
BELARUS      42.517730    34.257143    52.130435   119.900000
ROMANIA     117.018868    50.422764    62.020000   151.268293
CHINA       140.936170   140.936170   106.838710    96.000000
NEPAL       329.076923   427.800000   256.680000   207.000000
MEXICO      205.636364   251.333333   323.142857   357.157895

          WET_DAYS_MAY  WET_DAYS_JUN  WET_DAYS_JUL  WET_DAYS_AUG  \
COUNTRY
GERMANY      63.180000    42.979592    49.359375    46.800000
INDIA       294.775000   137.104651   102.530435    95.088710
TURKEY       44.297521    64.578313   153.142857    99.259259
PAKISTAN     66.566667    81.510204    72.618182    62.406250
IRAN         54.600000   491.400000   351.000000   351.000000
ALBANIA      89.495327    96.727273   199.500000   111.348837
EGYPT        95.800000   239.500000   479.000000   479.000000
BELARUS      39.966667    39.701987    43.442029    52.130435
ROMANIA      37.587879    36.269006    53.008547   110.750000
CHINA        65.584158    53.419355    51.750000    51.750000
NEPAL       160.425000   100.265625    66.154639    73.337143
MEXICO      178.578947    96.942857    67.188119    69.244898

          WET_DAYS_SEP  WET_DAYS_OCT  WET_DAYS_NOV  WET_DAYS_DEC  \
COUNTRY
GERMANY      57.963303    29.801887    85.378378    40.242038
INDIA       142.060241   294.775000   561.476190   982.583333
TURKEY      206.153846    99.259259    83.750000    58.260870
PAKISTAN    114.114286   998.500000   159.760000   181.545455
IRAN        819.000000   189.000000    42.362069    40.950000
ALBANIA      92.970874   105.230769   156.983607    57.000000
EGYPT              inf    95.800000    43.545455    59.875000
BELARUS      69.709302    45.416667    38.677419    44.738806
ROMANIA      88.600000    53.008547    88.600000    46.283582
CHINA        60.218182   112.271186   135.183673   236.571429
NEPAL       125.823529   458.357143  1166.727273   987.230769
MEXICO       72.191489   183.405405   295.043478   323.142857

          Total Precipitation
COUNTRY
GERMANY                   1.0
INDIA                     1.0
TURKEY                    1.0
PAKISTAN                  1.0
IRAN                      1.0
ALBANIA                   1.0
```

```
EGYPT                       1.0
BELARUS                     1.0
ROMANIA                     1.0
CHINA                       1.0
NEPAL                       1.0
MEXICO                      1.0
```

We can observe in the table for the wet_days in september, Egypt has an infinity point, having no wet days in the month of September. As such, the plot will not have any data for Egypt in September and it will connect the August and October directly

[46]:
```python
wet_day = sbs.relplot(data = df_wet.drop("Total Precipitation",axis=1).T, kind =␣
 ↪'line', height = 6, aspect = 2, markers = True, dashes = False)
wet_day.set_xticklabels(months)
wet_day.set_xlabels("Months")
wet_day.set_ylabels("Average precipitation per wet day")
wet_day.set(title = "Average precipitation per wet day per country in 2020.")
#Solution 2 end
```

[46]: <seaborn.axisgrid.FacetGrid at 0x287dcd6eeb0>



1.1.10 3.3

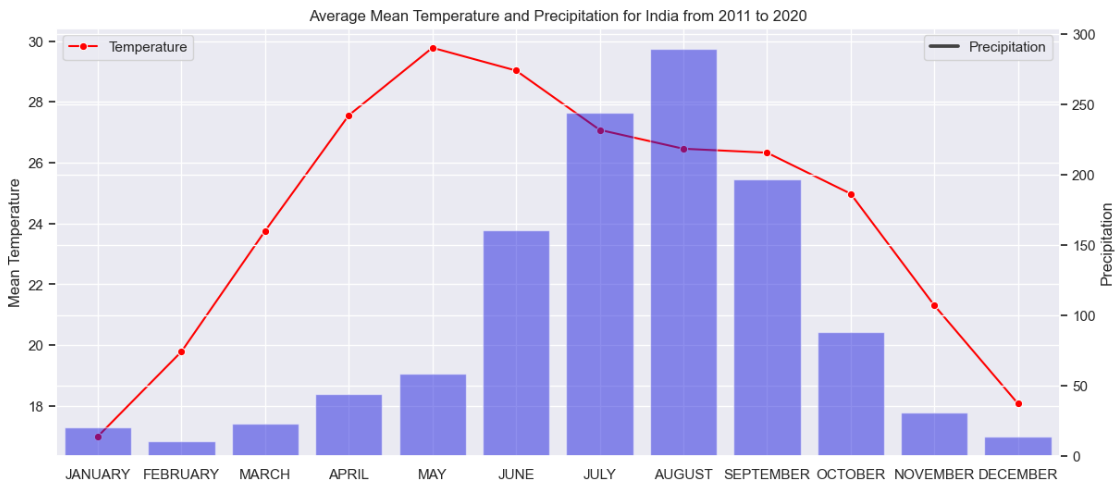
[47]:
```python
### Task 3 ###
db = df[(df['COUNTRY'] == 'INDIA') & (df['YEAR'].between(2011,2020))].
 ↪set_index("COUNTRY")
# Created dataset for india between 2011 and 2020
# We will plot the climate graphs based on the average for each month throught␣
 ↪the decade.
```

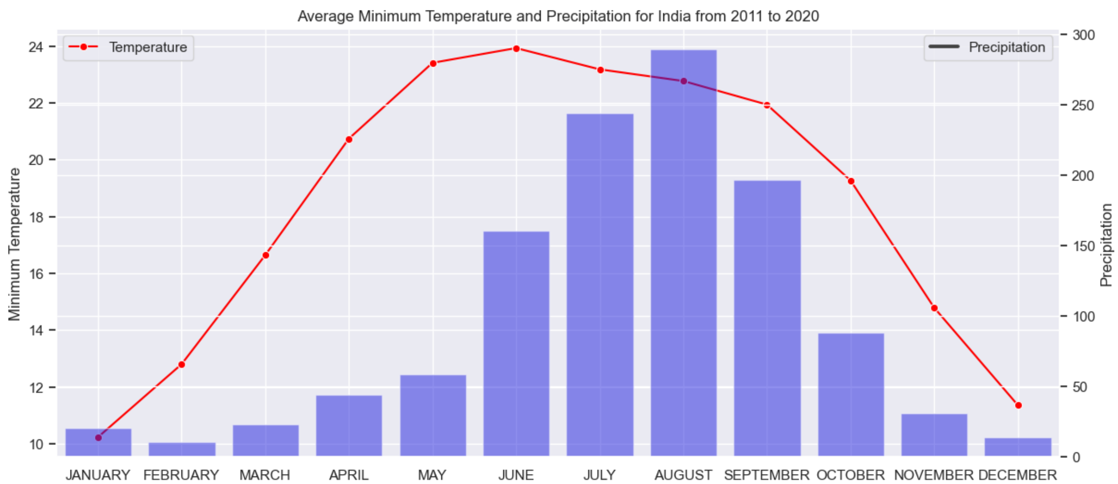
[48]:

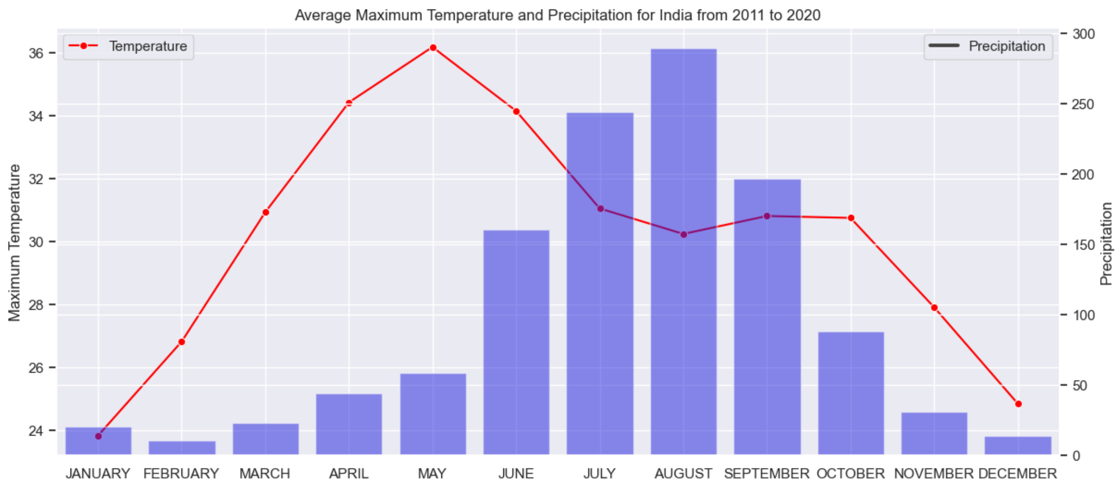
```
#Climate graphs
df_india = df[df['COUNTRY'] == 'INDIA'].query("YEAR >2010").set_index("YEAR").
↪drop("COUNTRY",axis=1)
df_india_mean_temp = df_india.iloc[:,:12]
df_india_precip_pc = df_precip.iloc[1:2].rename(columns = {'PRECIP_JAN':
↪'JANUARY', 'PRECIP_FEB':'FEBRUARY', 'PRECIP_MAR' : 'MARCH',
                                                          'PRECIP_APR':
↪'APRIL','PRECIP_MAY':'MAY','PRECIP_JUN':'JUNE','PRECIP_JUL':'JULY',
                                                          'PRECIP_AUG':
↪'AUGUST','PRECIP_SEP':'SEPTEMBER','PRECIP_OCT':'OCTOBER','PRECIP_NOV':
↪'NOVEMBER',
                                                          'PRECIP_DEC':
↪'DECEMBER'})

fig, ax1 = plt.subplots(figsize=(14,6))
sbs.lineplot(data=df_india_mean_temp.sum(axis=0)/10,color='red',marker =␣
↪'o',sort=False,ax=ax1)
ax1.set(ylabel="Mean Temperature", title = "Average Mean Temperature and␣
↪Precipitation for India from 2011 to 2020")
ax1.legend(['Temperature'], loc="upper left")
ax2 = ax1.twinx()
ax2.set(ylabel = "Precipitation")
sbs.barplot(data=df_india_precip_pc,ax=ax2,alpha=0.5,color='blue')
ax2.legend(['Precipitation'], loc = "upper right")


df_india_min_temp = df_india.iloc[:,16:28]
fig, ax1 = plt.subplots(figsize=(14,6))
sbs.lineplot(data=df_india_min_temp.sum(axis=0)/10,color='red',marker =␣
↪'o',sort=False,ax=ax1)
ax1.set(ylabel="Minimum Temperature", title = "Average Minimum Temperature and␣
↪Precipitation for India from 2011 to 2020")
ax1.legend(['Temperature'], loc="upper left")
ax2 = ax1.twinx()
ax2.set(ylabel = "Precipitation")
sbs.barplot(data=df_india_precip_pc,ax=ax2,alpha=0.5,color='blue')
ax2.legend(['Precipitation'], loc = "upper right")


df_india_max_temp = df_india.iloc[:,32:44]
fig, ax1 = plt.subplots(figsize=(14,6))
sbs.lineplot(data=df_india_max_temp.sum(axis=0)/10,color='red',marker =␣
↪'o',sort=False,ax=ax1)
ax1.set(ylabel="Maximum Temperature", title = "Average Maximum Temperature and␣
↪Precipitation for India from 2011 to 2020")
ax1.legend(['Temperature'], loc="upper left")
```

```
ax2 = ax1.twinx()
ax2.set(ylabel = "Precipitation")
sbs.barplot(data=df_india_precip_pc,ax=ax2,alpha=0.5,color='blue')
ax2.legend(['Precipitation'], loc = "upper right")
```

[48]: <matplotlib.legend.Legend at 0x287df80b100>



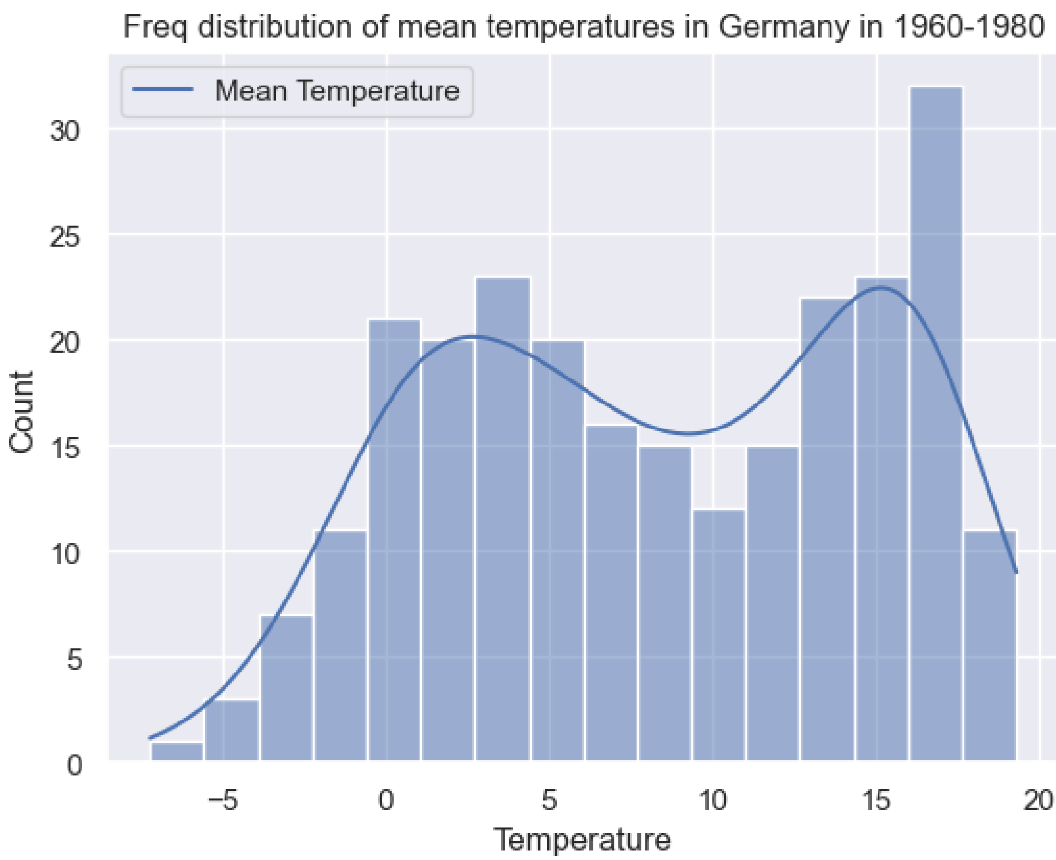




1.1.11 3.4

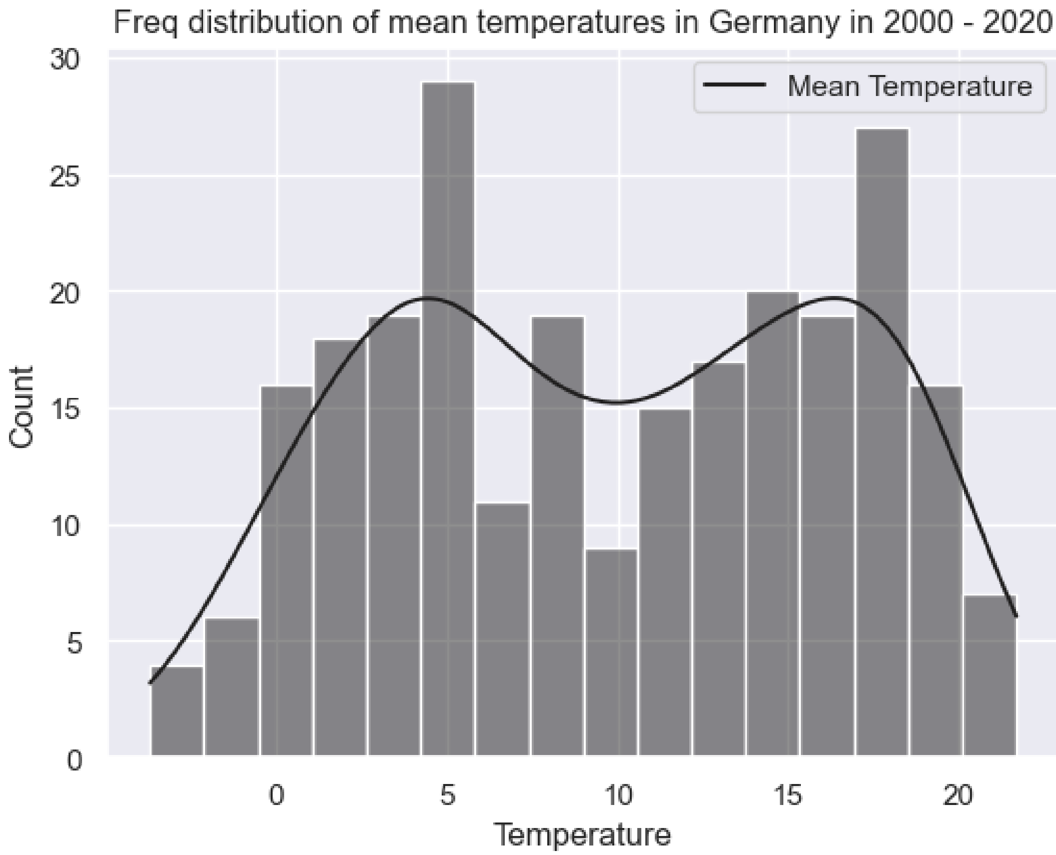
[49]:
```
#3.4
#Nr of bins = square root of total nr of data points (252 in our case)
#The binsize = (max_value-min_value)/(number of bins)
df_germany_data1 = df[df["COUNTRY"] == "GERMANY"].query("1959 < YEAR < 1981")
df_germany_data2 = df[df["COUNTRY"] == "GERMANY"].query("1999 < YEAR < 2022")
df_germany_tp1 = df_germany_data1.iloc[:,:14].drop(["COUNTRY","YEAR"],axis=1)
df_germany_tp2 = df_germany_data2.iloc[:,:14].drop(["COUNTRY","YEAR"],axis=1)
fig1 = sbs.histplot(data = df_germany_tp1.melt(),bins=16,binwidth=(19.3-(-7.2))/
 ↪16, kde = True)
fig1.set(title = "Freq distribution of mean temperatures in Germany in␣
 ↪1960-1980")
fig1.legend(['Mean Temperature'], loc = "upper left")
fig1.set(xlabel = "Temperature")
```

[49]:
```
[Text(0.5, 0, 'Temperature')]
```




```
[50]: fig2 = sbs.histplot(data = df_germany_tp2.melt(),bins=16,binwidth=(21.7-(-3.7))/
       ↪16, kde = True, palette = "icefire")
      fig2.set(title = "Freq distribution of mean temperatures in Germany in 2000 -␣
       ↪2020")
      fig2.legend(['Mean Temperature'], loc = "upper right")
      fig2.set(xlabel = "Temperature")
```

```
[50]: [Text(0.5, 0, 'Temperature')]
```



Task 4 [40 points] EDA Following the Titanic example from the lecture, we want to gain first insights into multivariate EDA. We want to see if the climate warming is different between countries. For this purpose, take the following steps using python to answer the question **whether the number of warmer/colder months (compared to 50 years ago) changes between countries and whether there is a difference between decades.**

For this task use the data from Egypt and Belarus starting from the year 1961.

1. For each month, calculate if it was warmer or colder compared to the same month 50 years ago.
2. Create two contingency tables of **total number of warmer and colder months per country** (one containing the absolute counts and the second one containing row and column proportions).
3. Create another two contingency tables of **total number of warmer and colder months per decade** (one containing the absolute counts and the second one containing row and column proportions).
4. Plot a histogram or bar chart that shows the **total number of warmer months by country and decade**. *Hint: The usage of different colors might help a lot!*
5. Now combine the contingency tables of task 4.2 and 4.3 (see Titanic example discussed in the EDA lecture), so that you have a subdivision into countries by decade, with absolute counts

and row/column proportions.
6. Calculate the expected frequencies f_e for each conjunct event in the contingency table from task 4.5 and create a copy of the table from task 4.5 containing the f_e values.
7. Calculate χ_{Egypt} and $\chi_{Belarus}$ and interpret.
8. What does a small χ value mean? What if it's zero? Explain.

1.1.12 Create the Proper dataset to answer the question 4.1

[51]:
```
decades1 = ["1961-1970" for i in range(0,120)]
decades2 = ["1971-1980" for i in range(0,120)]
decades3 = ["1981-1990" for i in range(0,120)]
decades4 = ["1991-2000" for i in range(0,120)]
decades5 = ["2001-2010" for i in range(0,120)]
decades6 = ["2011-2020" for i in range(0,120)]

decades = decades1 + decades2 + decades3 + decades4 + decades5 + decades6

final_decades = (decades + decades)
```

[52]:
```
df_egypt = df[df["COUNTRY"] == 'EGYPT'].iloc[:,:14].reset_index().
 ↪drop("index",axis=1)
```

[53]:
```
import calendar
m=calendar.month_name[1:]
year = []
months = m*60
result = []
country = ["EGYPT" for i in range(0,720)]
for i in range(60,120):
    for j in df_egypt.columns[2:]:
        #print(i,j)
        year.append(1901+i)
        if(df_egypt.loc[i,j] > df_egypt.loc[i-50,j]):
            result.append("Warmer")
        elif(df_egypt.loc[i,j] < df_egypt.loc[i-50,j]):
            result.append("Colder")
        elif((df_egypt.loc[i,j] == df_egypt.loc[i-50,j])):
            result.append("No Change")
data = {"COUNTRY":country,"YEAR":year,"DECADE":decades, "MONTH":months,"RESULT":
 ↪result}
df_egypt_warmer = pd.DataFrame(data)
df_41_egypt = df_egypt_warmer
```

[54]:
```
df_belarus = df[df["COUNTRY"] == 'BELARUS'].iloc[:,:14].reset_index().
 ↪drop("index",axis=1)
```

[55]:
```
import calendar
m=calendar.month_name[1:]
year = []
months = m*60
result = []
country = ["BELARUS" for i in range(0,720)]
for i in range(60,120):
    for j in df_belarus.columns[2:]:
        #print(i,j)
        year.append(1901+i)
        if(df_belarus.loc[i,j] > df_belarus.loc[i-50,j]):
            result.append("Warmer")
        elif(df_belarus.loc[i,j] < df_belarus.loc[i-50,j]):
            result.append("Colder")
        elif(df_belarus.loc[i,j] == df_belarus.loc[i-50,j]):
            result.append("No Change")
data = {"COUNTRY":country,"YEAR":year,"DECADE":decades, "MONTH":months,"RESULT":
 ↪result}
df_belarus_warmer = pd.DataFrame(data)
df_41_belarus = df_belarus_warmer
```

1.1.13 4.1

[56]:
```
df_41_egypt #df_41_egypt is the dataset that shows if every month starting from␣
 ↪1961 was warmer, colder, or had no change.
            #The Year 1961 implies that January of 1961 was warmer than Jaunary␣
 ↪of 1911
```

[56]:
```
    COUNTRY  YEAR     DECADE      MONTH  RESULT
0     EGYPT  1961  1961-1970    January  Warmer
1     EGYPT  1961  1961-1970   February  Warmer
2     EGYPT  1961  1961-1970      March  Colder
3     EGYPT  1961  1961-1970      April  Warmer
4     EGYPT  1961  1961-1970        May  Warmer
..      ...   ...        ...        ...     ...
715   EGYPT  2020  2011-2020     August  Warmer
716   EGYPT  2020  2011-2020  September  Warmer
717   EGYPT  2020  2011-2020    October  Warmer
718   EGYPT  2020  2011-2020   November  Warmer
719   EGYPT  2020  2011-2020   December  Warmer

[720 rows x 5 columns]
```

[57]:
```
df_41_belarus #df_41_belarus is the dataset that shows if every month starting␣
 ↪from 1961 was warmer, colder, or had no change.
              #The Year 1961 implies that January of 1961 was warmer than␣
 ↪Jaunary of 1911
```

[57]:

	COUNTRY	YEAR	DECADE	MONTH	RESULT
0	BELARUS	1961	1961-1970	January	Warmer
1	BELARUS	1961	1961-1970	February	Warmer
2	BELARUS	1961	1961-1970	March	Warmer
3	BELARUS	1961	1961-1970	April	Warmer
4	BELARUS	1961	1961-1970	May	Colder
..	...	...	...	...	...
715	BELARUS	2020	2011-2020	August	Warmer
716	BELARUS	2020	2011-2020	September	Warmer
717	BELARUS	2020	2011-2020	October	Warmer
718	BELARUS	2020	2011-2020	November	Warmer
719	BELARUS	2020	2011-2020	December	Warmer

[720 rows x 5 columns]

1.1.14 Preprocess the Data to remove the Months that did not have any change

[58]:
```
df_egypt_warmer.query("RESULT=='No Change'")
```

[58]:

	COUNTRY	YEAR	DECADE	MONTH	RESULT
6	EGYPT	1961	1961-1970	July	No Change
90	EGYPT	1968	1961-1970	July	No Change
116	EGYPT	1970	1961-1970	September	No Change
118	EGYPT	1970	1961-1970	November	No Change
125	EGYPT	1971	1971-1980	June	No Change
136	EGYPT	1972	1971-1980	May	No Change
187	EGYPT	1976	1971-1980	August	No Change
190	EGYPT	1976	1971-1980	November	No Change
195	EGYPT	1977	1971-1980	April	No Change
331	EGYPT	1988	1981-1990	August	No Change
354	EGYPT	1990	1981-1990	July	No Change
368	EGYPT	1991	1991-2000	September	No Change
420	EGYPT	1996	1991-2000	January	No Change
439	EGYPT	1997	1991-2000	August	No Change
440	EGYPT	1997	1991-2000	September	No Change
441	EGYPT	1997	1991-2000	October	No Change
551	EGYPT	2006	2001-2010	December	No Change
561	EGYPT	2007	2001-2010	October	No Change
653	EGYPT	2015	2011-2020	June	No Change

[59]:
```
df_egypt_warmer.
↪drop([6,90,116,118,125,136,187,190,195,331,354,368,420,439,440,441,551,561,653],inplace=True)
```

[60]:
```
df_belarus_warmer.query("RESULT=='No Change'")
```

[60]:

	COUNTRY	YEAR	DECADE	MONTH	RESULT
101	BELARUS	1969	1961-1970	June	No Change

```
171  BELARUS  1975  1971-1980     April  No Change
213  BELARUS  1978  1971-1980   October  No Change
214  BELARUS  1978  1971-1980  November  No Change
220  BELARUS  1979  1971-1980       May  No Change
313  BELARUS  1987  1981-1990  February  No Change
472  BELARUS  2000  1991-2000       May  No Change
621  BELARUS  2012  2011-2020   October  No Change
660  BELARUS  2016  2011-2020   January  No Change
```

[61]:
```
df_belarus_warmer.drop([101,171,213,214,220,313,472,621,660],inplace=True)
```

[62]:
```
final_data = pd.concat([df_egypt_warmer,df_belarus_warmer])
final_data   #Concatenate the data to create the final data set
```

[62]:
```
     COUNTRY  YEAR     DECADE      MONTH  RESULT
0      EGYPT  1961  1961-1970    January  Warmer
1      EGYPT  1961  1961-1970   February  Warmer
2      EGYPT  1961  1961-1970      March  Colder
3      EGYPT  1961  1961-1970      April  Warmer
4      EGYPT  1961  1961-1970        May  Warmer
..       ...   ...        ...        ...     ...
715  BELARUS  2020  2011-2020     August  Warmer
716  BELARUS  2020  2011-2020  September  Warmer
717  BELARUS  2020  2011-2020    October  Warmer
718  BELARUS  2020  2011-2020   November  Warmer
719  BELARUS  2020  2011-2020   December  Warmer

[1412 rows x 5 columns]
```

1.1.15 End of Data Preprocessing

1.1.16 4.2

[63]:
```
#4.2
#Contingency Tables per country
pd.crosstab(final_data.COUNTRY,final_data.RESULT,margins=True) #Table with␣
 ↪absolute count
```

[63]:
```
RESULT   Colder  Warmer   All
COUNTRY
BELARUS     294     417   711
EGYPT       291     410   701
All         585     827  1412
```

[64]:
```
pd.crosstab(final_data.COUNTRY,final_data.RESULT,margins=True, normalize =␣
 ↪'index') #Table with row normalization
```

[64]:

RESULT	Colder	Warmer
COUNTRY		
BELARUS	0.413502	0.586498
EGYPT	0.415121	0.584879
All	0.414306	0.585694

[65]:

```
pd.crosstab(final_data.COUNTRY,final_data.RESULT,margins=True, normalize =␣
↪'columns') #Table with Column Normalization
```

[65]:

RESULT	Colder	Warmer	All
COUNTRY			
BELARUS	0.502564	0.504232	0.503541
EGYPT	0.497436	0.495768	0.496459

[66]:

```
pd.crosstab(final_data.COUNTRY,final_data.RESULT,margins=True, normalize =␣
↪'all') #Table with 'All' Normalization
```

[66]:

RESULT	Colder	Warmer	All
COUNTRY			
BELARUS	0.208215	0.295326	0.503541
EGYPT	0.206091	0.290368	0.496459
All	0.414306	0.585694	1.000000

1.1.17 4.3

[67]:

```
#4.3
#Contingency Tables per decade
pd.crosstab(final_data.DECADE,final_data.RESULT,margins=True) #Table with␣
↪absolute count
```

[67]:

RESULT	Colder	Warmer	All
DECADE			
1961-1970	121	114	235
1971-1980	127	104	231
1981-1990	144	93	237
1991-2000	90	144	234
2001-2010	57	181	238
2011-2020	46	191	237
All	585	827	1412

[68]:

```
pd.crosstab(final_data.DECADE,final_data.RESULT,margins=True,normalize =␣
↪'index') #Table with row normalization
```

[68]:

RESULT	Colder	Warmer
DECADE		
1961-1970	0.514894	0.485106
1971-1980	0.549784	0.450216
1981-1990	0.607595	0.392405

```
1991-2000  0.384615  0.615385
2001-2010  0.239496  0.760504
2011-2020  0.194093  0.805907
All        0.414306  0.585694
```

[69]:
```python
pd.crosstab(final_data.DECADE,final_data.RESULT,margins=True, normalize =
↪'columns') #Table with Column Normalization
```

[69]:
```
RESULT       Colder    Warmer       All
DECADE
1961-1970  0.206838  0.137848  0.166431
1971-1980  0.217094  0.125756  0.163598
1981-1990  0.246154  0.112455  0.167847
1991-2000  0.153846  0.174123  0.165722
2001-2010  0.097436  0.218863  0.168555
2011-2020  0.078632  0.230955  0.167847
```

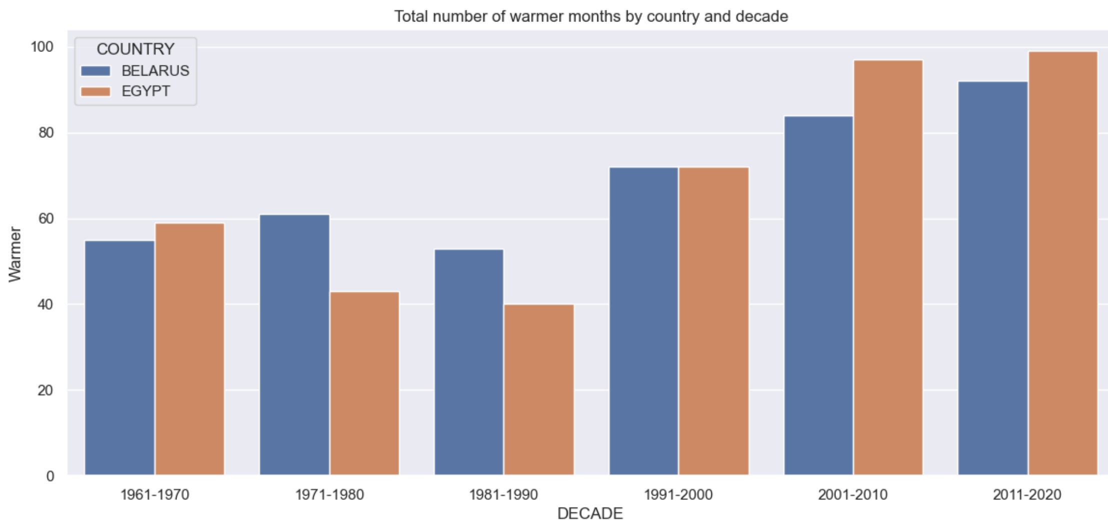
[70]:
```python
pd.crosstab(final_data.DECADE,final_data.RESULT,margins=True, normalize = 'all')
↪#Table with 'All' Normalization
```

[70]:
```
RESULT       Colder    Warmer       All
DECADE
1961-1970  0.085694  0.080737  0.166431
1971-1980  0.089943  0.073654  0.163598
1981-1990  0.101983  0.065864  0.167847
1991-2000  0.063739  0.101983  0.165722
2001-2010  0.040368  0.128187  0.168555
2011-2020  0.032578  0.135269  0.167847
All        0.414306  0.585694  1.000000
```

1.1.18 4.4

[71]:
```python
#4.4
cross_data = pd.crosstab([final_data.COUNTRY,final_data.DECADE],final_data.
↪RESULT,margins=True)
cross = cross_data.reset_index().drop(12)
fig, ax1 = plt.subplots(figsize=(14,6))
sbs.barplot(data=cross, x="DECADE", y="Warmer", hue="COUNTRY").set(title="Total
↪number of warmer months by country and decade")
```

[71]:
```
[Text(0.5, 1.0, 'Total number of warmer months by country and decade')]
```



1.1.19 4.5

[72]:
```python
#4.5
# Contingency tables per country and per decade. Combining tables from 4.2 and 4.
↪3
cross_data = pd.crosstab([final_data.COUNTRY,final_data.DECADE],final_data.
↪RESULT,margins=True)
cross_data
```

[72]:
```
RESULT              Colder  Warmer   All
COUNTRY DECADE
BELARUS 1961-1970       64      55   119
        1971-1980       55      61   116
        1981-1990       66      53   119
        1991-2000       47      72   119
        2001-2010       36      84   120
        2011-2020       26      92   118
EGYPT   1961-1970       57      59   116
        1971-1980       72      43   115
        1981-1990       78      40   118
        1991-2000       43      72   115
        2001-2010       21      97   118
        2011-2020       20      99   119
All                    585     827  1412
```

[73]:
```python
pd.crosstab([final_data.COUNTRY,final_data.DECADE],final_data.
↪RESULT,margins=True, normalize = 'columns') #Normalized per Columns
```

[73]:
```
RESULT              Colder    Warmer       All
COUNTRY DECADE
BELARUS 1961-1970  0.109402  0.066505  0.084278
        1971-1980  0.094017  0.073761  0.082153
        1981-1990  0.112821  0.064087  0.084278
        1991-2000  0.080342  0.087062  0.084278
        2001-2010  0.061538  0.101572  0.084986
        2011-2020  0.044444  0.111245  0.083569
EGYPT   1961-1970  0.097436  0.071342  0.082153
        1971-1980  0.123077  0.051995  0.081445
        1981-1990  0.133333  0.048368  0.083569
        1991-2000  0.073504  0.087062  0.081445
        2001-2010  0.035897  0.117291  0.083569
        2011-2020  0.034188  0.119710  0.084278
```

1.1.20 4.6

[74]:
```
#4.6
fe_data = cross_data.copy(deep=True)
fe_data = fe_data.reset_index()
fe_cold_total = 585
fe_warm_total = 827
for j in ["Colder","Warmer"]:
    for i in range(0,12):
        if(j=="Colder"):
            fe_data.loc[i,j] = (fe_data.loc[i,"All"]*fe_cold_total)/1412
        elif(j=="Warmer"):
            fe_data.loc[i,j] = (fe_data.loc[i,"All"]*fe_warm_total)/1412
fe_data.set_index(["COUNTRY", "DECADE"])
```

[74]:
```
RESULT                 Colder      Warmer   All
COUNTRY DECADE
BELARUS 1961-1970   49.302408   69.697592   119
        1971-1980   48.059490   67.940510   116
        1981-1990   49.302408   69.697592   119
        1991-2000   49.302408   69.697592   119
        2001-2010   49.716714   70.283286   120
        2011-2020   48.888102   69.111898   118
EGYPT   1961-1970   48.059490   67.940510   116
        1971-1980   47.645184   67.354816   115
        1981-1990   48.888102   69.111898   118
        1991-2000   47.645184   67.354816   115
        2001-2010   48.888102   69.111898   118
        2011-2020   49.302408   69.697592   119
All                585.000000  827.000000  1412
```

1.1.21 fe_data is the table which is filled with the expected frequencies

1.1.22 4.7

[75]:
```
#4.7
cross_data = cross_data.reset_index()
fe_data = fe_data.reset_index()
chi_squared_belarus = 0
for j in ["Colder","Warmer"]:
    for i in range(0,6):
        chi_squared_belarus += np.square(cross_data.loc[i,j]-fe_data.loc[i,j])/
 ↪fe_data.loc[i,j]
chi_squared_egypt = 0
for j in ["Colder","Warmer"]:
    for i in range(6,12):
        chi_squared_egypt += np.square(cross_data.loc[i,j]-fe_data.loc[i,j])/
 ↪fe_data.loc[i,j]
print("Chi Squared for Belarus is ",chi_squared_belarus)
print("Chi Squared for Egypt ypt is ",chi_squared_egypt)
```

```
Chi Squared for Belarus is  43.78812406853108
Chi Squared for Egypt ypt is  111.36431334863138
```

Higher chi values implies higher correlation in the data. As we see in our dataset, the value for Belarus is approx. 43, which shows Belarus is getting warmer over time, but for Egypt the value is approx. 111, which results in a higher change with passing time.

Since the chi values between Belarus and Egypt are different, this shows that the two countries are affected diffently with respect to time.

1.1.23 4.8

A zero chi squared value means that the expected frequency and observed frequency are exactly the same. This implies that the conjunct event of temperature and time would be mutually independent of each other. Implying that they have no correlation. For a small value, it means that the values are less dependent.