In [18]:

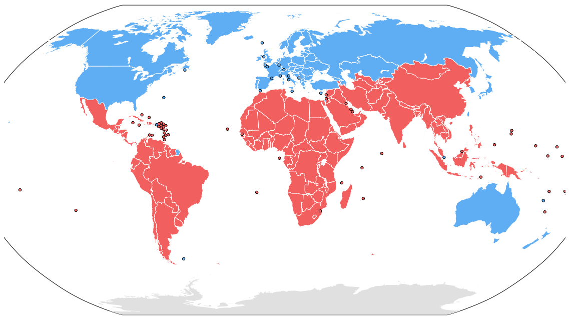
```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-pyt
hon
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all fil
es under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 5GB to the current directory (/kaggle/working/) that gets preserv
ed as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside
 of the current session
```

```
/kaggle/input/world-development-indicators/SeriesNotes.csv
/kaggle/input/world-development-indicators/Series.csv
/kaggle/input/world-development-indicators/Indicators.csv
/kaggle/input/world-development-indicators/Footnotes.csv
/kaggle/input/world-development-indicators/database.sqlite
/kaggle/input/world-development-indicators/hashes.txt
/kaggle/input/world-development-indicators/Country.csv
/kaggle/input/world-development-indicators/CountryNotes.csv
```

In [19]:

```
# Data Source: https://www.kaggle.com/worldbank/world-development-indicators
# Folder: 'world-development-indicators'
```

World Development Indicators



This week, we will be using an open dataset from [Kaggle (https://www.kaggle.com)](https://www.kaggle.com). It is [The World Development Indicators (https://www.kaggle.com/worldbank/world-development-indicators)](https://www.kaggle.com/worldbank/world-development-indicators) dataset obtained from the World Bank containing over a thousand annual indicators of economic development from hundreds of countries around the world.

This is a slightly modified version of the original dataset from [The World Bank (http://data.worldbank.org/data-catalog/world-development-indicators)](http://data.worldbank.org/data-catalog/world-development-indicators)

List of the [available indicators (https://www.kaggle.com/benhamner/d/worldbank/world-development-indicators/indicators-in-data)](https://www.kaggle.com/benhamner/d/worldbank/world-development-indicators/indicators-in-data) and a [list of the available countries (https://www.kaggle.com/benhamner/d/worldbank/world-development-indicators/countries-in-the-wdi-data)](https://www.kaggle.com/benhamner/d/worldbank/world-development-indicators/countries-in-the-wdi-data).

Step 1: Initial exploration of the Dataset

In [20]:

```
import pandas as pd
import numpy as np
import random
import matplotlib.pyplot as plt
%matplotlib inline
```

In [21]:

```
data = pd.read_csv('../input/world-development-indicators/Indicators.csv')
data.shape
```

Out[21]:

```
(5656458, 6)
```

This is a really large dataset, at least in terms of the number of rows. But with 6 columns, what does this hold?

In [22]:

```
data.head(10)
```

Out[22]:

	CountryName	CountryCode	IndicatorName	IndicatorCode	Year	Value
0	Arab World	ARB	Adolescent fertility rate (births per 1,000 wo...	SP.ADO.TFRT	1960	1.335609e+02
1	Arab World	ARB	Age dependency ratio (% of working-age populat...	SP.POP.DPND	1960	8.779760e+01
2	Arab World	ARB	Age dependency ratio, old (% of working-age po...	SP.POP.DPND.OL	1960	6.634579e+00
3	Arab World	ARB	Age dependency ratio, young (% of working-age ...	SP.POP.DPND.YG	1960	8.102333e+01
4	Arab World	ARB	Arms exports (SIPRI trend indicator values)	MS.MIL.XPRT.KD	1960	3.000000e+06
5	Arab World	ARB	Arms imports (SIPRI trend indicator values)	MS.MIL.MPRT.KD	1960	5.380000e+08
6	Arab World	ARB	Birth rate, crude (per 1,000 people)	SP.DYN.CBRT.IN	1960	4.769789e+01
7	Arab World	ARB	CO2 emissions (kt)	EN.ATM.CO2E.KT	1960	5.956399e+04
8	Arab World	ARB	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	1960	6.439635e-01
9	Arab World	ARB	CO2 emissions from gaseous fuel consumption (%...	EN.ATM.CO2E.GF.ZS	1960	5.041292e+00

Looks like it has different indicators for different countries with the year and value of the indicator.

How many UNIQUE country names are there ?

In [23]:

```
countries = data['CountryName'].unique().tolist()
len(countries)
```

Out[23]:

```
247
```

Are there same number of country codes ?

In [24]:

```
# How many unique country codes are there ? (should be the same #)
countryCodes = data['CountryCode'].unique().tolist()
len(countryCodes)
```

Out[24]:

```
247
```

Are there many indicators or few ?

In [25]:

```
# How many unique indicators are there ? (should be the same #)
indicators = data['IndicatorName'].unique().tolist()
len(indicators)
```

Out[25]:

```
1344
```

How many years of data do we have ?

In [26]:

```
# How many years of data do we have ?
years = data['Year'].unique().tolist()
len(years)
```

Out[26]:

```
56
```

What's the range of years?

In [27]:

```
print(min(years)," to ",max(years))
```

```
1960  to  2015
```

Indicators exploration

- Filter indicators using key words related to eduation and employment (e.g., education, school, employment...)

In [28]:

```
indicators_interest = []
for ind in indicators:
    if ('education' in ind.lower() or 'school' in ind.lower()) and 'unemploy' in ind.lo
wer():
        print(ind)
        indicators_interest.append(ind)

print('\nNumber of indicators of interest: ', len(indicators_interest))
```

```
Unemployment with primary education (% of total unemployment)
Unemployment with primary education, female (% of female unemployment)
Unemployment with primary education, male (% of male unemployment)
Unemployment with secondary education (% of total unemployment)
Unemployment with secondary education, female (% of female unemployment)
Unemployment with secondary education, male (% of male unemployment)
Unemployment with tertiary education (% of total unemployment)
Unemployment with tertiary education, female (% of female unemployment)
Unemployment with tertiary education, male (% of male unemployment)

Number of indicators of interest:  9
```

Step 2: Reasearch question

- How the level of education influences unemployment? Evaluate how the situation evolved over time.
- Is there a difference between male and female? (in a selection of countries)

Step 3: Data filtering

Subset a dataframe from data containing indicators of interest for slected countries and period of time.

In [29]:

```python
countries_interest1 = ['France', 'Italy'] # 2 European countries
countries_interest2 = ['Egypt, Arab Rep.', 'Tunisia'] # 2 Arabic North African countries
years_interest = [i for i in range(1975, 2016)]

# Creating a filter to extract the data for chosen indicators, countries and period of time
condition1 = data['CountryName'].isin(countries_interest1 + countries_interest2)
condition2 = data['Year'].isin(years_interest)
condition3 = data['IndicatorName'].isin(indicators_interest)

filt = condition1 & condition2 & condition3

df = data[filt]

df.head(20)
```

Out[29]:

	CountryName	CountryCode	IndicatorName	IndicatorCode	Year	Value
1874139	Tunisia	TUN	Unemployment with primary education (% of tota...	SL.UEM.PRIM.ZS	1989	51.200001
1874140	Tunisia	TUN	Unemployment with primary education, female (%...	SL.UEM.PRIM.FE.ZS	1989	45.700001
1874141	Tunisia	TUN	Unemployment with primary education, male (% o...	SL.UEM.PRIM.MA.ZS	1989	53.400002
1874142	Tunisia	TUN	Unemployment with secondary education (% of to...	SL.UEM.SECO.ZS	1989	25.799999
1874143	Tunisia	TUN	Unemployment with secondary education, female ...	SL.UEM.SECO.FE.ZS	1989	25.400000
1874144	Tunisia	TUN	Unemployment with secondary education, male (%...	SL.UEM.SECO.MA.ZS	1989	26.000000
1874145	Tunisia	TUN	Unemployment with tertiary education (% of tot...	SL.UEM.TERT.ZS	1989	1.300000
1874146	Tunisia	TUN	Unemployment with tertiary education, female (...	SL.UEM.TERT.FE.ZS	1989	1.500000
1874147	Tunisia	TUN	Unemployment with tertiary education, male (% ...	SL.UEM.TERT.MA.ZS	1989	1.300000
2176825	Italy	ITA	Unemployment with primary education (% of tota...	SL.UEM.PRIM.ZS	1992	57.799999
2176826	Italy	ITA	Unemployment with primary education, female (%...	SL.UEM.PRIM.FE.ZS	1992	54.099998
2176827	Italy	ITA	Unemployment with primary education, male (% o...	SL.UEM.PRIM.MA.ZS	1992	62.200001
2176828	Italy	ITA	Unemployment with secondary education (% of to...	SL.UEM.SECO.ZS	1992	37.700001
2176829	Italy	ITA	Unemployment with secondary education, female ...	SL.UEM.SECO.FE.ZS	1992	41.299999

	CountryName	CountryCode	IndicatorName	IndicatorCode	Year	Value
2176830	Italy	ITA	Unemployment with secondary education, male (%...	SL.UEM.SECO.MA.ZS	1992	33.400002
2176831	Italy	ITA	Unemployment with tertiary education (% of tot...	SL.UEM.TERT.ZS	1992	4.500000
2176832	Italy	ITA	Unemployment with tertiary education, female (...	SL.UEM.TERT.FE.ZS	1992	4.600000
2176833	Italy	ITA	Unemployment with tertiary education, male (% ...	SL.UEM.TERT.MA.ZS	1992	4.400000
2299875	Italy	ITA	Unemployment with primary education (% of tota...	SL.UEM.PRIM.ZS	1993	61.500000
2299876	Italy	ITA	Unemployment with primary education, female (%...	SL.UEM.PRIM.FE.ZS	1993	57.500000

Check quality of data (absence of missing values)

In [30]:

```
print(df.isna().any())
```

```
CountryName      False
CountryCode      False
IndicatorName    False
IndicatorCode    False
Year             False
Value            False
dtype: bool
```

Further filtering

Building a filter to look at chosen indicator values for a given country (below is an example)

In [31]:

```
extract_conditions = ((df['CountryName'] == 'Egypt, Arab Rep.') &
                      (df['IndicatorName'].isin(['Unemployment with primary education (
% of total unemployment)',
                                                 'Unemployment with secondary education
(% of total unemployment)',
                                                 'Unemployment with tertiary education
 (% of total unemployment)'])))

df[extract_conditions].sort_values(by=['IndicatorCode', 'Year'])
```

Out[31]:

	CountryName	CountryCode	IndicatorName	IndicatorCode	Year	Value
4547018	Egypt, Arab Rep.	EGY	Unemployment with primary education (% of tota...	SL.UEM.PRIM.ZS	2008	3.000000
4726454	Egypt, Arab Rep.	EGY	Unemployment with primary education (% of tota...	SL.UEM.PRIM.ZS	2009	4.000000
4908399	Egypt, Arab Rep.	EGY	Unemployment with primary education (% of tota...	SL.UEM.PRIM.ZS	2010	3.500000
5091153	Egypt, Arab Rep.	EGY	Unemployment with primary education (% of tota...	SL.UEM.PRIM.ZS	2011	7.500000
5266942	Egypt, Arab Rep.	EGY	Unemployment with primary education (% of tota...	SL.UEM.PRIM.ZS	2012	8.700000
5435487	Egypt, Arab Rep.	EGY	Unemployment with primary education (% of tota...	SL.UEM.PRIM.ZS	2013	4.100000
4547021	Egypt, Arab Rep.	EGY	Unemployment with secondary education (% of to...	SL.UEM.SECO.ZS	2008	62.299999
4726457	Egypt, Arab Rep.	EGY	Unemployment with secondary education (% of to...	SL.UEM.SECO.ZS	2009	55.700001
4908402	Egypt, Arab Rep.	EGY	Unemployment with secondary education (% of to...	SL.UEM.SECO.ZS	2010	53.200001
5091156	Egypt, Arab Rep.	EGY	Unemployment with secondary education (% of to...	SL.UEM.SECO.ZS	2011	50.000000
5266943	Egypt, Arab Rep.	EGY	Unemployment with secondary education (% of to...	SL.UEM.SECO.ZS	2012	51.900002
5435490	Egypt, Arab Rep.	EGY	Unemployment with secondary education (% of to...	SL.UEM.SECO.ZS	2013	47.099998
4547024	Egypt, Arab Rep.	EGY	Unemployment with tertiary education (% of tot...	SL.UEM.TERT.ZS	2008	31.700001
4726460	Egypt, Arab Rep.	EGY	Unemployment with tertiary education (% of tot...	SL.UEM.TERT.ZS	2009	35.500000

	CountryName	CountryCode	IndicatorName	IndicatorCode	Year	Value
4908405	Egypt, Arab Rep.	EGY	Unemployment with tertiary education (% of tot...	SL.UEM.TERT.ZS	2010	39.700001
5091159	Egypt, Arab Rep.	EGY	Unemployment with tertiary education (% of tot...	SL.UEM.TERT.ZS	2011	32.099998
5266944	Egypt, Arab Rep.	EGY	Unemployment with tertiary education (% of tot...	SL.UEM.TERT.ZS	2012	33.200001
5435493	Egypt, Arab Rep.	EGY	Unemployment with tertiary education (% of tot...	SL.UEM.TERT.ZS	2013	31.100000

Step 4: Plotting data

A function is defined to plot the indicators as function of time. Matplotlib function "*plot*" is appropriate in this case to show the evolution of the indicator over the years.

Axis will be set identically for all graphs to facilitate comparisons.

In [32]:

```
def unemployment_plot(data_edu_unemploy, country_list, indicator_list, leg_dict, line_s
tyle):
    '''Plotting function which shows the evolution of the indicator over time. It produ
ces several graphs in one run (with similar layout and look)
    Arguments:
    - data_edu_unemploy = dataframe with the data to plot
    - country_list = list of countries for which a plot is expected
    - indicator_list = list of indicators for which a plot is expected
    - leg_dict = dictionnary to allow short names for the plotted indicators
    - line_stype = list of line styles to apply to the data series'''

    for i in range(len(country_list)):
        fig, ax = plt.subplots()
        leg = []
        for j in range(len(indicator_list)):
            # Subset the data_edu_employ dataframe to extract data for a given country
 and a given indicator
            extract_conditions = ((data_edu_unemploy['CountryName'] == country_list[i])
&
                                  (data_edu_unemploy['IndicatorName'] == indicator_list
[j]))
            df_ext = data_edu_unemploy[extract_conditions]

            # Plot the data for the country (indicator value vs. time period)
            ax.plot(df_ext['Year'], df_ext['Value'], line_style[j])

            # Set axis limits and labels
            ax.axis([1990, 2015,0,65])
            ax.set_xlabel('Year', fontsize=14)
            ax.set_ylabel('% of total unemployment', fontsize=14)

            # Set title
            ax.set_title(country_list[i], fontsize=18)

            # Set legend
            leg.append(leg_dict[indicator_list[j]])
            ax.legend(leg, loc=3)

            # Turn grid on
            ax.grid(True)
```

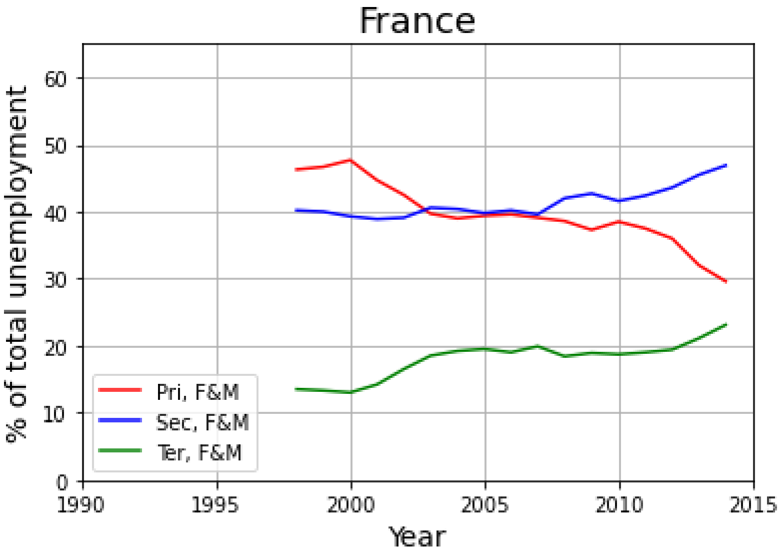
1. Exploring evolution of Unemployment vs. Education (male & female)

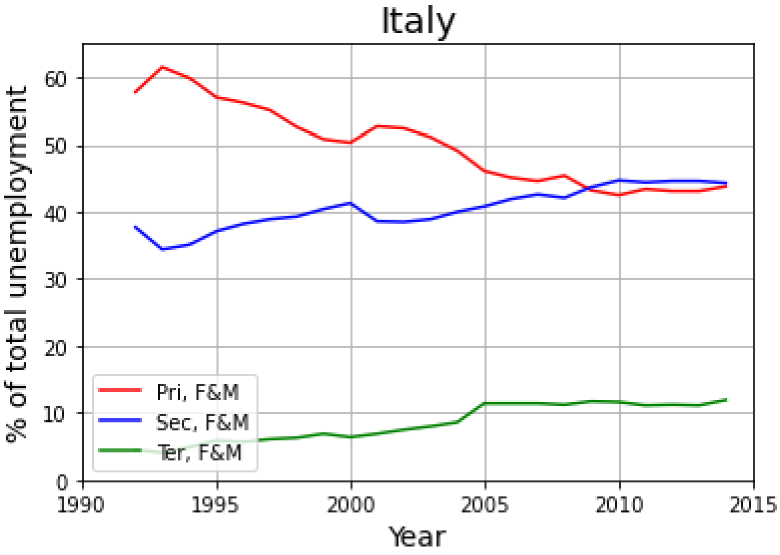
The indicators to plot are:

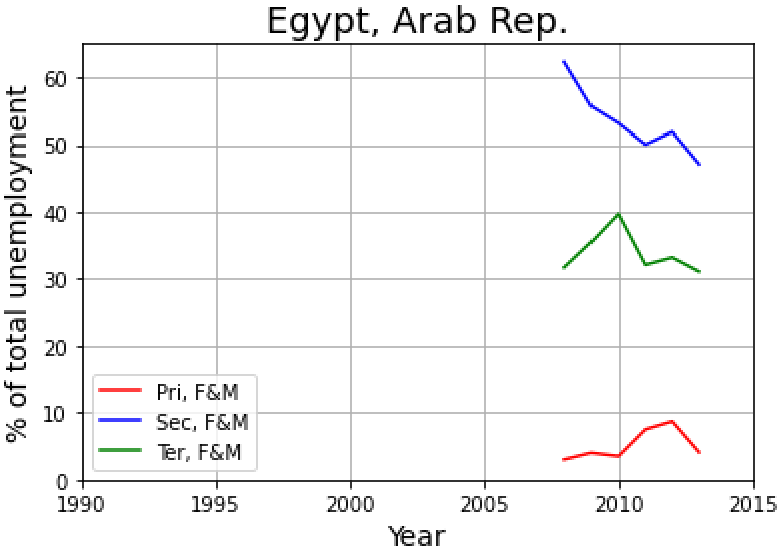
- "*Unemployment with primary education (% of total unemployment)*"
- "*Unemployment with secondary education (% of total unemployment)*"
- "*Unemployment with tertiary education (% of total unemployment)*"

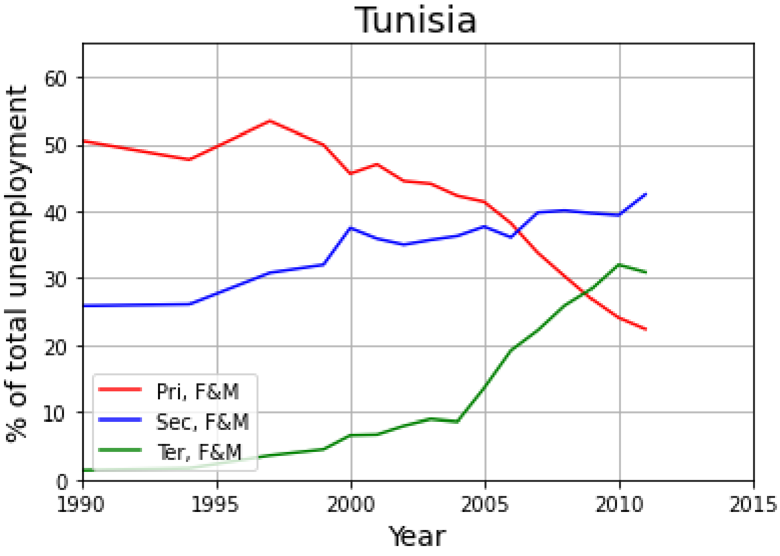
In [33]:

```
# Define the dictionnary for the legend
leg_short = ['Pri, F&M', 'Pri, F', 'Pri, M',
             'Sec, F&M', 'Sec, F', 'Sec, M',
             'Ter, F&M', 'Ter, F', 'Ter, M']
leg_dict = dict(zip(indicators_interest, leg_short))

# Define line styles for the 3 indicators
line_style = ['r', 'b', 'g']

# Prepare list for the countries and the indicators
country_list = countries_interest1 + countries_interest2
pos = 0 # positional index for slicing indicators_interest list
indicator_list = indicators_interest[pos:len(indicators_interest):3]

# Plotting the data
unemployment_plot(df, country_list, indicator_list, leg_dict, line_style)
```


France
% of total unemployment
0
10
20
30
40
50
60
1990
1995
2000
2005
2010
2015
Year
Pri, F&M
Sec, F&M
Ter, F&M


Italy
% of total unemployment
0
10
20
30
40
50
60
1990
1995
2000
2005
2010
2015
Year
Pri, F&M
Sec, F&M
Ter, F&M


Egypt, Arab Rep.
% of total unemployment
0
10
20
30
40
50
60
1990
1995
2000
2005
2010
2015
Year
Pri, F&M
Sec, F&M
Ter, F&M


Tunisia
% of total unemployment
0
10
20
30
40
50
60
1990
1995
2000
2005
2010
2015
Year
Pri, F&M
Sec, F&M
Ter, F&M

Observations:

In France and Italy:

1. Highly similar indicators
2. Population with *tertiary* education are less likely to be unemployed
3. However, from 2005 to 2015, the unemployment proportion of *tertiary* educated population tend to increase while the unemployment proportion of *primary* educated population tend to decrease. The unemployment proportion of people with *secondary* education remains nearly stable over time.

In Tunisia:

1. Similar trends as France and Italy are observed. However the amplitude of changes is larger.
2. From 2000 to 2015, the unemployment proportion of people with *tertiary* education has greatly increased (and to some extent the unemployment proportion of people with *seconday* education). Within the same period, the unemployment proportion of people with *primary* education has drastically decreased

In Egypt:

1. Less data is available (2008 to 2013)
2. Surprisingly, the sequence of the indicators is very different: the unemployment proportion of population with *secondary* education is the highest. But then it is followed by unemployment proportion of people with *tertiary* education. Finally, unemployment proportion of people with *primary* education is the lowest.

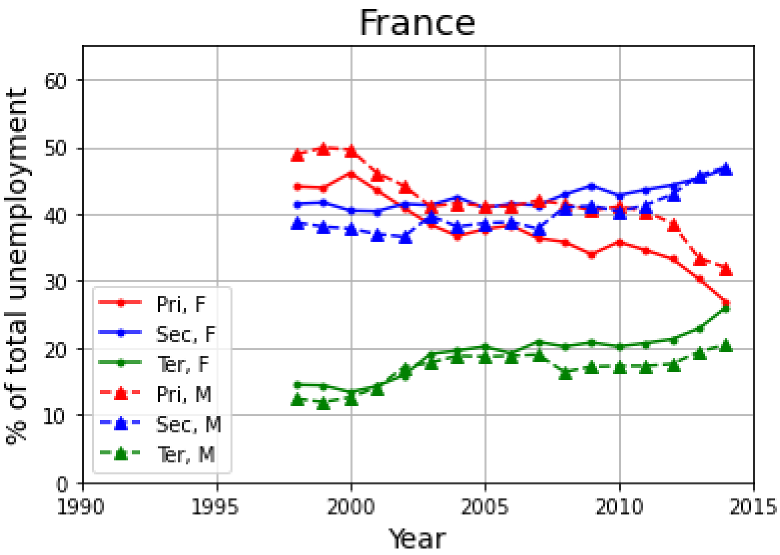
2. Exploring differences between male and female regarding Unemployment vs. Education

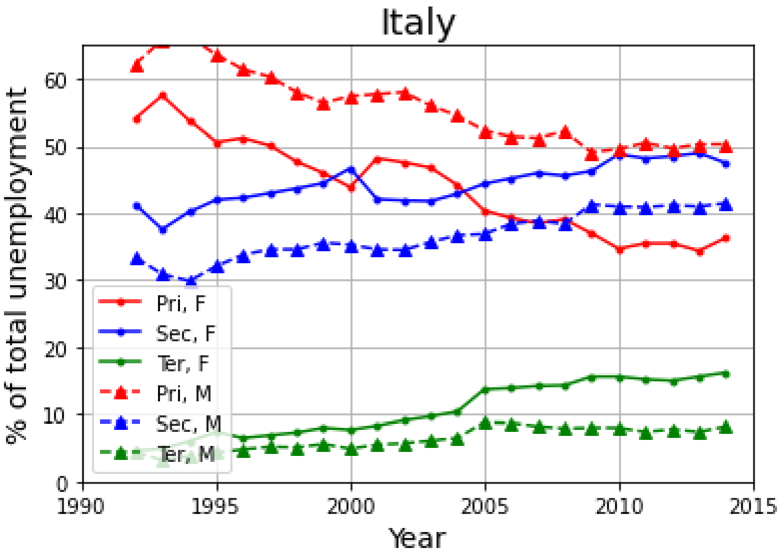
The indicators to plot are:

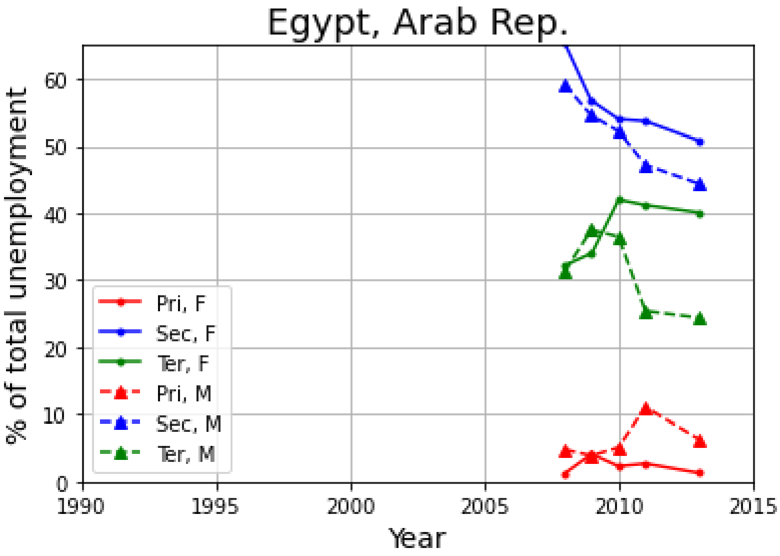
- *Unemployment with primary education, female (% of female unemployment)*
- *Unemployment with primary education, male (% of male unemployment)*
- *Unemployment with secondary education, female (% of female unemployment)*
- *Unemployment with secondary education, male (% of male unemployment)*
- *Unemployment with tertiary education, female (% of female unemployment)*
- *Unemployment with tertiary education, male (% of male unemployment)*

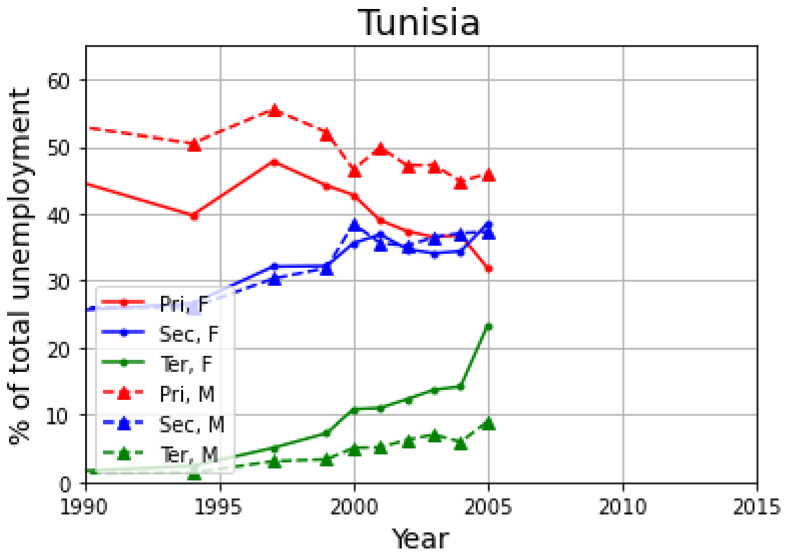
In [34]:

```
# Define line styles for the 6 indicators
line_style = ['r.-', 'b.-', 'g.-', 'r^--', 'b^--', 'g^--', ]

# Prepare list for the countries and the indicators
country_list = countries_interest1 + countries_interest2
pos = 1 # positional index for slicing indicators_interest list
indicator_list = indicators_interest[pos:len(indicators_interest):3] + indicators_interest[pos + 1:len(indicators_interest):3]

# Plotting the data
unemployment_plot(df, country_list, indicator_list, leg_dict, line_style)
```


France
% of total unemployment
0
10
20
30
40
50
60
1990
1995
2000
2005
2010
2015
Year
Pri, F
Sec, F
Ter, F
Pri, M
Sec, M
Ter, M

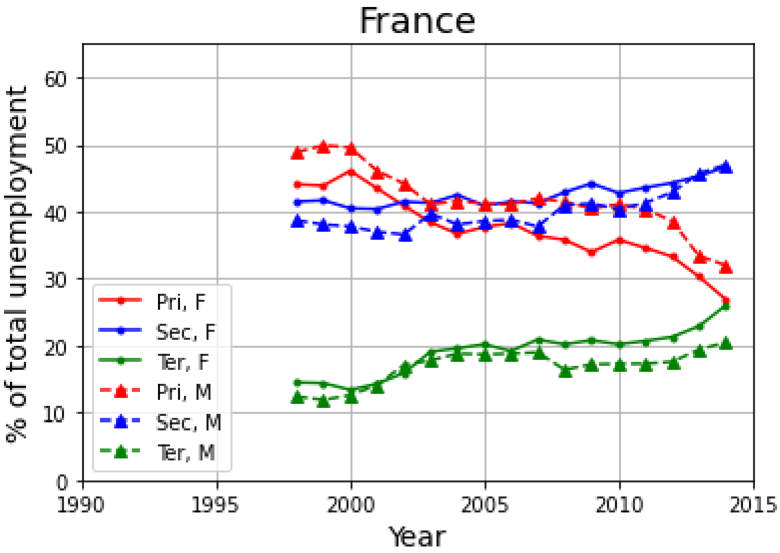

Italy
% of total unemployment
0
10
20
30
40
50
60
1990
1995
2000
2005
2010
2015
Year
Pri, F
Sec, F
Ter, F
Pri, M
Sec, M
Ter, M

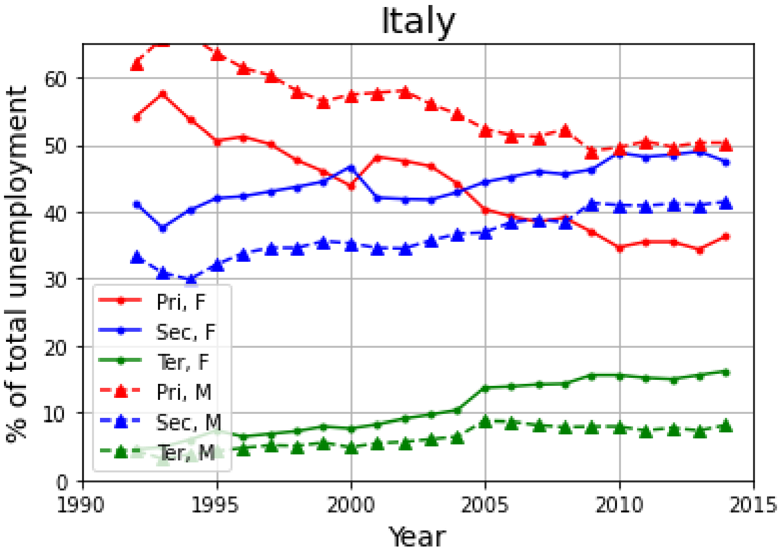

Egypt, Arab Rep.
% of total unemployment
0
10
20
30
40
50
60
1990
1995
2000
2005
2010
2015
Year
Pri, F
Sec, F
Ter, F
Pri, M
Sec, M
Ter, M

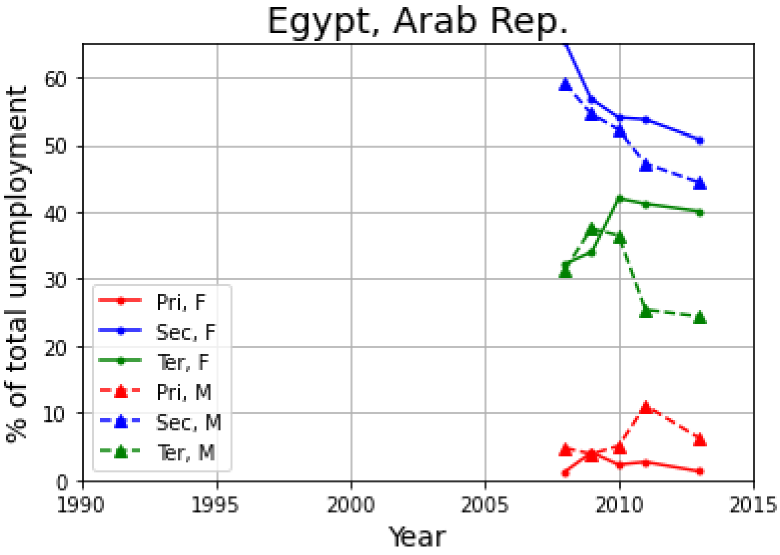

Tunisia
% of total unemployment
Year
0
10
20
30
40
50
60
1990
1995
2000
2005
2010
2015
Pri, F
Sec, F
Ter, F
Pri, M
Sec, M
Ter, M

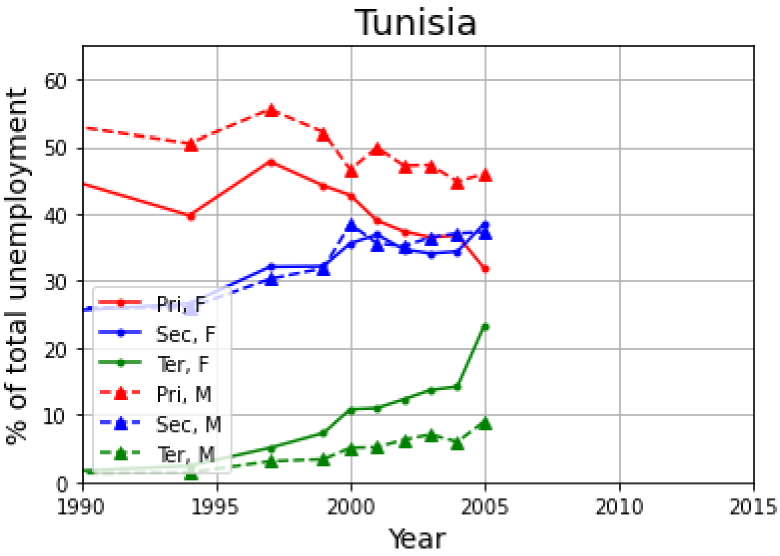
In [35]:

```
# Define line styles for the 6 indicators
line_style = ['r.-', 'b.-', 'g.-', 'r^--', 'b^--', 'g^--', ]

# Prepare list for the countries and the indicators
country_list = countries_interest1 + countries_interest2
pos = 1 # positional index for slicing indicators_interest list
indicator_list = indicators_interest[pos:len(indicators_interest):3] + indicators_inter
est[pos + 1:len(indicators_interest):3]

# Plotting the data
unemployment_plot(df, country_list, indicator_list, leg_dict, line_style)
```


France
% of total unemployment
0
10
20
30
40
50
60
1990
1995
2000
2005
2010
2015
Year
Pri, F
Sec, F
Ter, F
Pri, M
Sec, M
Ter, M


Italy
% of total unemployment
0
10
20
30
40
50
60
1990
1995
2000
2005
2010
2015
Year
Pri, F
Sec, F
Ter, F
Pri, M
Sec, M
Ter, M


Egypt, Arab Rep.
% of total unemployment
0
10
20
30
40
50
60
1990
1995
2000
2005
2010
2015
Year
Pri, F
Sec, F
Ter, F
Pri, M
Sec, M
Ter, M



Observations:

In all countries:

1. Women with *secondary* or *tertiary* education are more affected by unemployment than men. Situation particularly visible for Italy and Tunisia
2. The situation is the opposite for *primary* educated population: in this population, higher proportion of men is affected by unemployment
3. In France, Italy and Tunisia, for *teriaty* educated population, the unemployment gap between male and female tend to increase