Data Methods for Health Research (DMHR) Assignment

Important Note:

```
1) To excute the code, first download data files from the following urls:
* practice: uploaded to github
* patient: 'https://files.digital.nhs.uk/71/B59D99/gp-reg-pat-prac-all.csv'
* prescribing: 'https://files.digital.nhs.uk/38/03EC1C/T201804PDPI%20BNFT.CSV'

* country_codes: 'https://www.who.int/healthinfo/statistics/country_codes.zip'
* population: 'https://www.who.int/healthinfo/statistics/Pop.zip'
* mortality: 'https://www.who.int/healthinfo/statistics/Morticd10_part1.zip'
           'https://www.who.int/healthinfo/statistics/Morticd10_part2.zip'
2) Then, unzip the data files and save all the data files at the same directory as the Jupyter Notebook
```

In [3]:
```
#preliminaries
import pandas as pd
import numpy as np

%matplotlib inline
import matplotlib.pyplot as plt

from math import floor
```

In [4]:
```
path = './'
```

Assignment A - GP Practice Prescribing dataset

Overview of Assignment A

1) Assignment A uses data of GP Practice Prescribing from NHS to analyse drug prescription and corresponding costs. The results can provide guideline for achieving “efficiency savings”in GP practices

2) There are mainly 3 files used in this session and are read into 3 DataFrames named 'practice', 'patient' and 'prescribing':

- practice: practice code, practice name and geographic information of GP practices, to select practices in a given geographic locality
- patient: practice code and muber of patients to find the number of patients of each practice
- prescribing: practice code to identify practice, bnf code and bnf name to identify drug, as well as actual cost and quantity which gives information of drug prescription.

3) Data preparation include reading in files, analysing missing values and outliers, as well as summarizing data. These process are conducted both at the beginning and later in in the assignment. Data prepareation enables reliable results based on quality dataset.

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0. Data preparation

0.1 Read in files to pandas dataframes

In [53]:

```
# 1. Read in the practice information data file to a pandas dataframe

# Create custom column names and read in the file using the column names as the header
filename=path + 'T201804ADDR+BNFT.CSV'
cols = ['timePeriod', 'practice_code', 'practice_name', 'practice_organization', 'street', 'city',
'area', 'postcode']
practice = pd.read_csv(filename, sep=',',header=None, names=cols,index_col=False).rename(columns=l
ambda x: x.strip())

# Explore the data using built-in methods
practice.head()
```

Out[53]:

	timePeriod	practice_code	practice_name	practice_organization	street	city	
0	201804	A81001	THE DENSHAM SURGERY	THE HEALTH CENTRE	LAWSON STREET	STOCKTON-ON-TEES	C
1	201804	A81002	QUEENS PARK MEDICAL CENTRE	QUEENS PARK MEDICAL CTR	FARRER STREET	STOCKTON ON TEES	C
2	201804	A81004	BLUEBELL MEDICAL CENTRE	TRIMDON AVENUE	ACKLAM	MIDDLESBROUGH	
3	201804	A81005	SPRINGWOOD SURGERY	SPRINGWOOD SURGERY	RECTORY LANE	GUISBOROUGH	
4	201804	A81006	TENNANT STREET MEDICAL PRACTICE	TENNANT ST MEDICAL PRACT	TENNANT STREET	STOCKTON-ON-TEES	C

In [449]:
```
# 2. Read in the Number of Patients Registered data file to a pandas dataframe
filename_patient=path+'gp-reg-pat-prac-all.csv'
cols2 = ['publication', 'extract_date', 'type', 'ccg_code', 'ons_code', 'code', 'postcode', 'sex',
'age', 'number_of_patients']
patient = pd.read_csv(filename_patient, header=None, names=cols2, index_col=False, skiprows=1).ren
ame(columns=lambda x: x.strip())

patient.head()
```

Out[449]:

	publication	extract_date	type	ccg_code	ons_code	code	postcode	sex	age	numbe
0	GP_PRAC_PAT_LIST	01APR2018	GP	00C	E38000042	A83005	DL1 3RT	ALL	ALL	11826
1	GP_PRAC_PAT_LIST	01APR2018	GP	00C	E38000042	A83006	DL3 6HZ	ALL	ALL	8044
2	GP_PRAC_PAT_LIST	01APR2018	GP	00C	E38000042	A83010	DL3 9JP	ALL	ALL	14070
3	GP_PRAC_PAT_LIST	01APR2018	GP	00C	E38000042	A83013	DL1 4YL	ALL	ALL	11298
4	GP_PRAC_PAT_LIST	01APR2018	GP	00C	E38000042	A83031	DL3 8SQ	ALL	ALL	10109

In [55]:
```
# 3. Read in the prescribing information data file to a pandas dataframe
filename=path + 'T201804PDPI+BNFT.CSV'
cols = ['sha', 'pct', 'practice', 'bnf_code', 'bnf_name', 'items', 'nic', 'act_cost', 'quantity',
'period']
prescribing =  pd.read_csv(filename, header=None, names=cols, index_col=False, skiprows=1).rename(
columns=lambda x: x.strip())

prescribing.head()
```

Out[55]:

	sha	pct	practice	bnf_code	bnf_name	items	nic	act_cost	quantity	period
0	Q44	RTV	Y04937	0401010Z0AAAAAA	Zopiclone_Tab 7.5mg	6	1.56	2.12	63	201804
1	Q44	RTV	Y04937	0401020K0AAAHAH	Diazepam_Tab 2mg	4	0.87	1.15	73	201804
2	Q44	RTV	Y04937	0401020K0AAAIAI	Diazepam_Tab 5mg	2	0.46	0.56	35	201804
3	Q44	RTV	Y04937	0402010ABAAABAB	Quetiapine_Tab 25mg	1	2.60	2.52	14	201804
4	Q44	RTV	Y04937	0402010ADAAAAAA	Aripiprazole_Tab 10mg	1	1.53	1.53	14	201804

0.2 Check out the missing values

In [283]:
```
# Replace null values with python-readable NaN, so that the count() method is applicable, the init
ial dataframe is not changed
patient_missing=patient.replace('^\s+$', np.nan, regex=True)
# count non-NA/null values of each object
patient_missing.count(), patient_missing.shape
```

Out[283]:
```
(publication          7241
 extract_date         7241
 type                 7241
 ccg_code             7241
 ons_code             7241
 code                 7241
 postcode             7241
 sex                  7241
 age                  7241
 number_of_patients   7241
 dtype: int64, (7241, 10))
```

In [285]:
```
prescribing_missing=prescribing.replace('^\s+$', np.nan, regex=True)
prescribing_missing.count(), prescribing_missing.shape
```

Out[285]:
```
(sha         9748354
 pct         9748354
 practice    9748354
 bnf_code    9748354
 bnf_name    9748354
 items       9748354
 nic         9748354
 act_cost    9748354
 quantity    9748354
 period      9748354
 dtype: int64, (9748354, 10))
```

In [286]:
```
practice_missing=practice.replace('^\s+$', np.nan, regex=True)
practice_missing.count(),practice_missing.shape
```

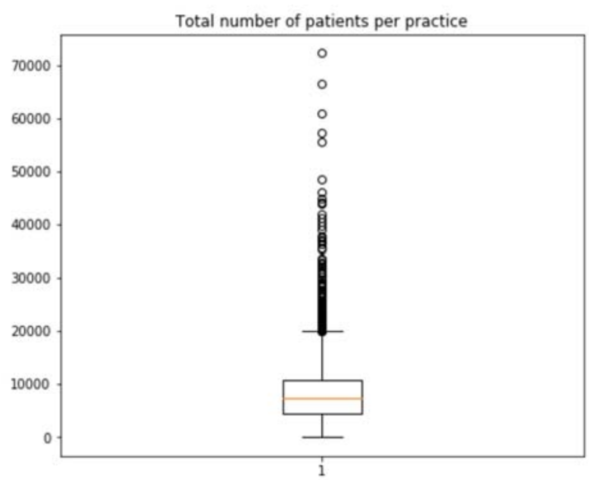
Out[286]:
```
(timePeriod               9578
 practice_code            9578
 practice_name            9578
 practice_organization    9574
 street                   8890
 city                     9215
 area                     7660
 postcode                 9578
 dtype: int64, (9578, 8))
```

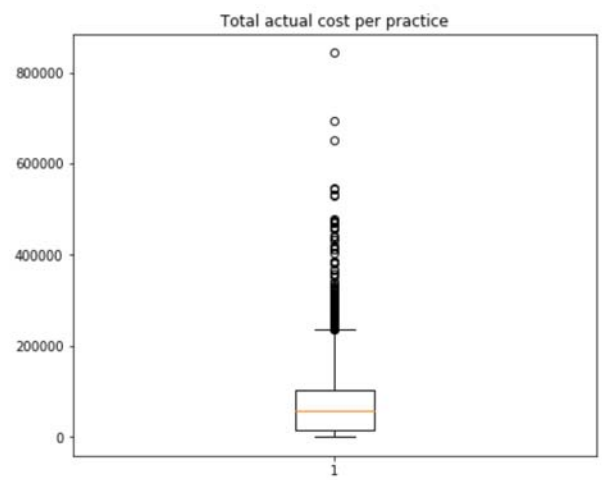
Missing value analysis:

- No missing value is observed in dataframes 'patient' and 'practice'.
- Most missing values exist in columns 'street', 'city' and 'area' of dataframe 'practice'. Therefore, it is necessary to include variable 'postcode' for identifying GP practices in a given geographic locality.
- There is no missing value in column 'code' of dataframe 'patient', column 'practice' of dataframe 'prescribing' or column 'practice_code' of dataframe 'practice', which all represent the unique identifier codes of GP practices. Therefore, the identifier code is a matching variable of high quality for linking these dataframes.

0.3 Check out the outliers

In [60]:
```
fig = plt.figure(figsize=(16,6))

# Plot a box plot of total number of patient per UK practice
fig1 = plt.subplot(121)
x1 = patient.number_of_patients.values
plt.boxplot(x1)
plt.title('Total number of patients per practice')

# Calculate total actual cost per UK Practice
act_cost_UK = pd.DataFrame(prescribing.groupby(prescribing.practice).apply(lambda subf: subf['act_
cost'].sum()))
act_cost_UK.columns=['total_actual_cost']
# Reseting the index
act_cost_UK.reset_index(inplace=True)

# plot a box plot of total number of patients per UK practice
fig2 = plt.subplot(122)
x2 = act_cost_UK.total_actual_cost.values
plt.boxplot(x2)
plt.title('Total actual cost per practice')

plt.show()
plt.close()
```





Outlier detection and manipulation:

- It can be observed from the boxplots that there exist extremely huge numbers. However, they are not necessarily outliers. For example, the practice Nexus Health Group, which has 72,227 registered patients in this dataset, is reported to serve 60,000 patients in 1st August 2016. So they are reasonably large and are not excluding for Question 1 to 3 for counting the total values.
- In question 4, while calculating relative costs per patient, extreme values would largely effect the mean values. Therefore, the outliers should be excluded from the dataset, which will be explained in part 4 in detail.

0.4 Summarize data

In [72]:
```
summarize=[practice['practice_code'].count(), prescribing['quantity'].sum(),patient['number_of_pat
ients'].mean(), patient['number_of_patients'].std()]
summarize
```

Out[72]:
```
[9578, 6955996497, 8153.514017400911, 5184.888435306803]
```

Data summary:

- There are in total 9,578 recorded practices, and 6,955,996,497 recorded prescriptions. There are on average 8,154 patients per practice. The standard deviation is 5185 which indicates high level of variation.

1. Identify all GP practices located in London. For those practices, describe:

- the total number of patients registered
- the total number of prescriptions
- the total actual cost of these prescriptions (using the ACT COST column)
- the top 10 most frequent drugs prescribed
- the bottom 10 less frequent drugs prescribed

Identigy all GP practices located in London

The selection rule is: include the practice if the name of its area contains 'LONDON' or its postcode starts with 'E', 'EC', 'N', 'NW', 'SE', 'SW', 'W' or 'WC'

- As is explained in part 0.1, it is reasonalbe to use columns 'area' and 'postcode' to select GP practices located in London.
- The name of area should include 'LONDON' but not necessarilly be 'LONDON', because it can be validated that areas such as 'FINCHLEY LONDON' also belong to london.
- The practice should meet at least one criterion but not necessarilly both, because there are many missing values in column 'area'

In [64]:
```
# Identify all GP practices located in London.
selected_area='LONDON'
postcode_regex='E\d|EC\d|N\d|NW\d|SE\d|SW\d|W\d|WC\d'
# Select practices whose areas contain 'LONDON' or postcodes belong to City of London
practice_london=practice[practice.area.str.match('[^\d]*'+selected_area)|practice.postcode.str.match(postcode_regex)]
practice_london.head()
```

Out[64]:

	timePeriod	practice_code	practice_name	practice_organization	street	
1873	201804	E83003	OAKLEIGH ROAD HEALTH CENTRE	OAKLEIGH ROAD HEALTH CTR	280 OAKLEIGH ROAD NORTH	WHETSTONE
1874	201804	E83005	LICHFIELD GROVE SURGERY	64 LICHFIELD GROVE		FINCHLEY
1875	201804	E83006	GREENFIELD MEDICAL CENTRE	GREENFIELD MEDICAL CENTRE	143-145 CRICKLEWOOD LANE	CRICKLEWO
1876	201804	E83007	SQUIRES LANE MEDICAL PRACTICE	2 SQUIRES LANE		FINCHLEY
1877	201804	E83008	HEATHFIELDE MEDICAL CENTRE	HEATHFIELDE MEDICAL CTR	LYTTLETON ROAD FINCHLEY	BARNET

For those practices, desctibe:

1.1 The total number of patients registered

In [450]:
```
# Link dataframe 'patient' and 'practice_london' matching by practice code to identify number of p
atients registered at each London practice
patient_london = pd.merge(practice_london, patient[['code', 'number_of_patients']], left_on='pract
ice_code' , right_on='code')
patient_london.head()
```

Out[450]:

	timePeriod	practice_code	practice_name	practice_organization	street	city
0	201804	E83003	OAKLEIGH ROAD HEALTH CENTRE	OAKLEIGH ROAD HEALTH CTR	280 OAKLEIGH ROAD NORTH	WHETSTONE
1	201804	E83005	LICHFIELD GROVE SURGERY	64 LICHFIELD GROVE		FINCHLEY
2	201804	E83006	GREENFIELD MEDICAL CENTRE	GREENFIELD MEDICAL CENTRE	143-145 CRICKLEWOOD LANE	CRICKLEWOOD
3	201804	E83007	SQUIRES LANE MEDICAL PRACTICE	2 SQUIRES LANE		FINCHLEY
4	201804	E83008	HEATHFIELDE MEDICAL CENTRE	HEATHFIELDE MEDICAL CTR	LYTTLETON ROAD FINCHLEY	BARNET

In [451]:
```
# Calculate the total number of patients for all London practices
total_number_of_patients_london = sum(patient_london.number_of_patients)
total_number_of_patients_london
```

Out[451]: 6026298L

- Q1.1 The total number of patients registered at all GP practices located in London is 6,026,298.

1.2 The total number of prescriptions

Note: According to documentation, bnf_code/bnf_name is unique (no duplicated rows) for each drug and practice, and all prescriptions of each drug is recorded in one row. So we should sum up the values of column 'quantity' rather than count the number of rows to calculate the total number of prescriptions.

In [70]:
```
# Link dataframe 'prescribing' and 'practice_london' matching by practice code to select prescribi
ng data for London practices
prescribing_london=pd.merge(prescribing[['practice', 'bnf_code', 'bnf_name', 'act_cost', 'quantity
']],practice_london[['practice_code', 'practice_name']],left_on='practice',right_on='practice_code
')#.copy(deep=True)
prescribing_london.head()
```

Out[70]:

	practice	bnf_code	bnf_name	act_cost	quantity	practice_code	practice_name
0	Y04681	0101021B0BEADAJ	Gaviscon Infant_Sach 2g (Dual Pack) S/F	4.48	15	Y04681	WATFORD CARE ALLIANCE
1	Y04681	0106040M0BBAAAA	Movicol_Pdr Sach 13.8g (Lem & Lim)	5.13	20	Y04681	WATFORD CARE ALLIANCE
2	Y04681	0106040M0BBAJAB	Movicol_Paed Pdr Sach 6.9g (Choc)	4.07	30	Y04681	WATFORD CARE ALLIANCE
3	Y04681	0106040N0AAABAB	Phos Enem_(For B) 128ml Stnd Tube	36.92	10	Y04681	WATFORD CARE ALLIANCE
4	Y04681	0106040R0BBAAAF	Micralax_Micro-Enem 5ml	3.88	10	Y04681	WATFORD CARE ALLIANCE

In [73]:
```
# Calculate the total number of prescriptions for all London practices
total_number_of_prescriptions_london=prescribing_london.quantity.sum()
total_number_of_prescriptions_london
```

Out[73]: 526975959

- Q1.2 The total number of prescriptions across all GP practices located in London is 526,975,959

1.3 The total actual cost of these prescriptions

In [75]:
```
# Calculate the total actual cost of prescriptions for all London practices
total_act_cost_london=sum(prescribing_london.act_cost)
total_act_cost_london
```

Out[75]: 44914570.21000154

- Q1.3 The total actual cost of prescriptions across all GP practices located in London is 44,914,570

1.4 The top 10 most frequent drugs prescribed

In [83]:
```
# Sum up total quantity prescribed per drug grouping by bnf_name which is unique for each drug and practice according to documentation
quantity_london=pd.DataFrame(prescribing_london.groupby(prescribing_london.bnf_name).apply(lambda subf: subf['quantity'].sum()))

# Rename the column
quantity_london.columns=['total_quantity_prescribed_per_drug']
# Reset the index
quantity_london.reset_index(inplace=True)

# Sort the data according to the total quantity prescribed
quantity_london_sorted=quantity_london.sort_values('total_quantity_prescribed_per_drug', axis=0, ascending=False, kind='quicksort', na_position='last')
# Select the top 10 most frequent drugs prescribed
top_10_london=quantity_london_sorted.head(10)
# Reset the index
top_10_london=top_10_london.reset_index(drop=True)

# The top 10 most frequent drugs prescribed
top_10_london
```

Out[83]:

	bnf_name	total_quantity_prescribed_per_drug
0	Ensure Plus_Milkshake Style Liq (9 Flav)	17618168
1	Metformin HCl_Tab 500mg	12067995
2	Fortisip Bottle_Liq (8 Flav)	10435984
3	Lactulose_Soln 3.1g-3.7g/5ml	9573152
4	Paracet_Tab 500mg	7953529
5	Dermol 500_Lot	6926000
6	Ensure Compact_Liq (4 Flav)	6887822
7	Fresubin 2kcal_Drink (6 Flav)	6723152
8	Fortisip Compact_Liq (8 Flav)	5610000
9	Omeprazole_Cap E/C 20mg	4834655

- Q1.4 The top 10 most frequent drugs prescribed across all GP practices located in London:

Rank	Drug	Total quantity prescribed
1	Ensure Plus_Milkshake Style Liq (9 Flav)	17618168
2	Metformin HCl_Tab 500mg	12067995
3	Fortisip Bottle_Liq (8 Flav)	10435984
4	Lactulose_Soln 3.1g-3.7g/5ml	9573152
5	Paracet_Tab 500mg	7953529
6	Dermol 500_Lot	6926000
7	Ensure Compact_Liq (4 Flav)	6887822
8	Fresubin 2kcal_Drink (6 Flav)	6723152
9	Fortisip Compact_Liq (8 Flav)	5610000
10	Omeprazole_Cap E/C 20mg	4834655

1.5 The bottom 10 less frequent drugs prescribed

In [114]:

```
# The bottom 10 most frequent drugs prescribed
bottom_10_london=quantity_london_sorted.tail(10)
# Reset the index
bottom_10_london = bottom_10_london.reset_index(drop=True)

# the bottom 10 less frequent drugs prescribed
bottom_10_london
```

Out[114]:

	bnf_name	total_quantity_prescribed_per_drug
0	Tritace_Titration Pack (Tab 2.5/5/10mg)	1
1	Botulinum A Toxin_Inj Pdr 50u Vl	1
2	Botulinum A Toxin_Inj Pdr 200u Vl	1
3	Botulinum A Toxin_Inj Pdr 100u Vl	1
4	Hypafix gentle touch 10cm x 2m Surg Adh	1
5	Bonviva_Inj 3mg/3ml Pfs	1
6	Blumont Hypromellose 0.3% Eye Dps 10ml	1
7	Blue Dot Retention S/Cloth SurgTape 10cm	1
8	Mediven harmony Class 1 A/Sleeve + Shoul	1
9	Methotrexate_Inj 7.5mg/0.3ml Pfs	0

It can be observed that the total quantity of more than 10 drugs are equally small. To identify the least frequent drugs prescribed:

In [116]:
```
# Select the drugs, whose total number of prescription is 0 or 1
bottom_10_london_update = quantity_london_sorted[quantity_london_sorted.total_quantity_prescribed_per_drug<=1]
# Reset the index
bottom_10_london_update = bottom_10_london_update.reset_index(drop=True)

# The least frequent drugs prescribed
bottom_10_london_update.tail(10)
```

Out[116]:

	bnf_name	total_quantity_prescribed_per_drug
238	Tritace_Titration Pack (Tab 2.5/5/10mg)	1
239	Botulinum A Toxin_Inj Pdr 50u Vl	1
240	Botulinum A Toxin_Inj Pdr 200u Vl	1
241	Botulinum A Toxin_Inj Pdr 100u Vl	1
242	Hypafix gentle touch 10cm x 2m Surg Adh	1
243	Bonviva_Inj 3mg/3ml Pfs	1
244	Blumont Hypromellose 0.3% Eye Dps 10ml	1
245	Blue Dot Retention S/Cloth SurgTape 10cm	1
246	Mediven harmony Class 1 A/Sleeve + Shoul	1
247	Methotrexate_Inj 7.5mg/0.3ml Pfs	0

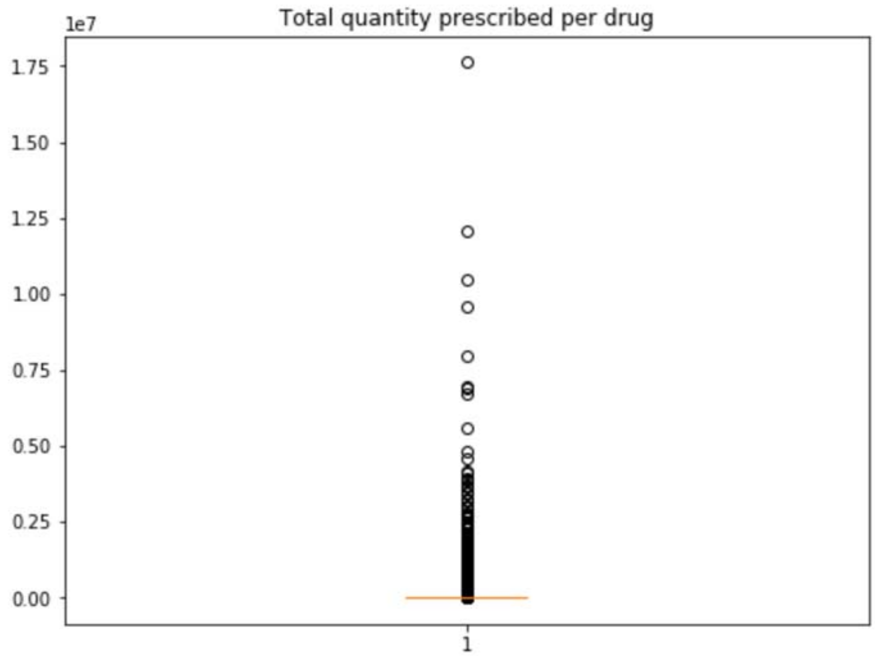
In [146]:
```
# Count the number of drugs
bottom_10_london_update.bnf_name.count()
```

Out[146]: 248

- Q1.5 In this dataset, the least frequent drug prescribed is Methotrexate_Inj 7.5mg/0.3ml Pfs. There are 247 drugs which are prescribed only once.

Discussion

In [122]:
```
# Plot a box plot of total quantity prescribed per drug to detect possible outliers
fig = plt.figure(figsize=(8,6))

x = quantity_london_sorted.total_quantity_prescribed_per_drug.values
plt.boxplot(x)
plt.title('Total quantity prescribed per drug')

plt.show()
plt.close()
```



In [125]:
```
# Check if the quantity of Ensure Plus_Milkshake Style Liq (9 Flav) prescribed is unreasonably lar
ge
top_frequent = prescribing_london[prescribing_london.bnf_name=='Ensure Plus_Milkshake Style Liq (9
Flav)']
top_frequent.head()
```

Out[125]:

	practice	bnf_code	bnf_name	act_cost	quantity	practice_code	practice_name
2174	E83003	090402000BBRRA0	Ensure Plus_Milkshake Style Liq (9 Flav)	399.35	76800	E83003	OAKLEIGH ROAD HEALTH CENTRE
3470	E83005	090402000BBRRA0	Ensure Plus_Milkshake Style Liq (9 Flav)	280.34	42000	E83005	LICHFIELD GROVE SURGERY
5761	E83007	090402000BBRRA0	Ensure Plus_Milkshake Style Liq (9 Flav)	204.68	39400	E83007	SQUIRES LANE MEDICAL PRACTICE
6971	E83008	090402000BBRRA0	Ensure Plus_Milkshake Style Liq (9 Flav)	215.48	35200	E83008	HEATHFIELDE MEDICAL CENTRE
8368	E83009	090402000BBRRA0	Ensure Plus_Milkshake Style Liq (9 Flav)	704.66	135600	E83009	PHGH DOCTORS

The box plot indicate possible outliers which are extremely large. However, it can be observed that the quantity of the top frequent drug prescribed is generally large. So the results of Question 1.4 and 1.5 are reasonable.

2. Repeat the previous instructions, this time for the city of Cambridge. Discuss andcompare your findings with the answers for London in question 1 above using descriptive statistics.

Identigy all GP practices located in city of Cambridge

The selection rule is: include the practice if the name of its city is 'Cambridge'.

- The postcode of city of Cambridge starts with 'CB'. However it also refers to other area outside city of Cambridge. Therefore, the column 'postcode' is not used to select GP practices located in city of Cambridge.
- The column 'city' is used instead of 'area' and the name of city should be 'Cambridge', so that the subset refer to the city of Cambridge rather than a larger area of Cambridgeshire.

In [131]:
```
# Identify all GP practices located in City of Cambridge.
selected_city='CAMBRIDGE'
# Select practices whose city is 'CAMBRIDGE', '\s*' is used to eliminate the effect of spaces
practice_cambridge=practice[(practice.city.str.match('\s*'+selected_city))]
practice_cambridge.head()
```

Out[131]:

	timePeriod	practice_code	practice_name	practice_organization	street	city
1455	201804	D81001	LENSFIELD MEDICAL PRACTICE	LENSFIELD MEDICAL PRAC.	48 LENSFIELD ROAD	CAMBRIDGE
1456	201804	D81002	HUNTINGDON ROAD SURGERY	HUNTINGDON ROAD SURGERY	1 HUNTINGDON ROAD	CAMBRIDGE
1457	201804	D81003	YORK STREET MEDICAL PRACTICE	YORK STREET MED PRACT.	146-148 YORK STREET	CAMBRIDGE
1459	201804	D81005	NEWNHAM WALK SURGERY	NEWNHAM WALK SURGERY	WORDSWORTH GROVE	CAMBRIDGE
1462	201804	D81009	SHELFORD MEDICAL PRACTICE	SHELFORD MEDICAL PRACTICE	ASHEN GREEN GRT SHELFORD	CAMBRIDGE

For those practices, desctibe:

2.1 The total number of patients registered

In [452]:
```
# Link dataframe 'patient' and 'practice_cambridge' matching by practice code to identify number o
f patients registered at each Cambridge practice
patient_cambridge = pd.merge(practice_cambridge, patient[['code', 'number_of_patients']], left_on=
'practice_code' , right_on='code')
patient_cambridge.head()
```

Out[452]:

	timePeriod	practice_code	practice_name	practice_organization	street	city	
0	201804	D81001	LENSFIELD MEDICAL PRACTICE	LENSFIELD MEDICAL PRAC.	48 LENSFIELD ROAD	CAMBRIDGE	C/
1	201804	D81002	HUNTINGDON ROAD SURGERY	HUNTINGDON ROAD SURGERY	1 HUNTINGDON ROAD	CAMBRIDGE	
2	201804	D81003	YORK STREET MEDICAL PRACTICE	YORK STREET MED PRACT.	146-148 YORK STREET	CAMBRIDGE	C/
3	201804	D81005	NEWNHAM WALK SURGERY	NEWNHAM WALK SURGERY	WORDSWORTH GROVE	CAMBRIDGE	C/
4	201804	D81009	SHELFORD MEDICAL PRACTICE	SHELFORD MEDICAL PRACTICE	ASHEN GREEN GRT SHELFORD	CAMBRIDGE	C/

In [458]:
```
# Calculate the total number of patients for all Cambridge practices
total_number_of_patients_cambridge = sum(patient_cambridge.number_of_patients)
total_number_of_patients_cambridge
```

Out[458]: 300885L

- Q2.1 The total number of patients registered at all GP practices located in city of Cambridge is 300,885.

2.2 The total number of prescriptions

In [135]:

```
# Link dataframe 'prescribing' and 'practice_cambridge' matching by practice code to select prescribing data for Cambridge practices
prescribing_cambridge=pd.merge(prescribing[['practice', 'bnf_code', 'bnf_name', 'act_cost', 'quantity']],practice_cambridge[['practice_code', 'practice_name']],left_on='practice',right_on='practice_code')#.copy(deep=True)
prescribing_cambridge.head()
```

Out[135]:

	practice	bnf_code	bnf_name	act_cost	quantity	practice_code	practice_name
0	D81001	0101021B0AAAHAH	Alginate_Raft-Forming Oral Susp S/F	11.29	2300	D81001	LENSFIELD MEDICAL PRACTICE
1	D81001	0101021B0AAALAL	Sod Algin/Pot Bicarb_Susp S/F	13.91	1450	D81001	LENSFIELD MEDICAL PRACTICE
2	D81001	0101021B0BEACAH	Gaviscon_Liq Orig Aniseed Relief	11.10	1000	D81001	LENSFIELD MEDICAL PRACTICE
3	D81001	0101021B0BEADAJ	Gaviscon Infant_Sach 2g (Dual Pack) S/F	8.96	30	D81001	LENSFIELD MEDICAL PRACTICE
4	D81001	0101021B0BEAUA0	Gaviscon P/Mint_Tab Chble	27.57	336	D81001	LENSFIELD MEDICAL PRACTICE

In [150]:

```
# Calculate the total number of prescriptions for all Cambridge practices
total_number_of_prescriptions_cambridge=prescribing_cambridge.quantity.sum()
total_number_of_prescriptions_cambridge
```

Out[150]: 24332260

- Q2.2 The total number of prescriptions across all GP practices located in city of Cambridge is 24,332,260

2.3 The total actual cost of these prescriptions

In [141]:

```
# Calculate the total actual cost of prescriptions for all Cambridge practices
total_act_cost_cambridge=sum(prescribing_cambridge.act_cost)
total_act_cost_cambridge
```

Out[141]: 2344091.249999998

- Q2.3 The total actual cost of prescriptions across all GP practices located in city of Cambridge is 2,344,091

2.4 The top 10 most frequent drugs prescribed

In [142]:
```
# Sum up total quantity prescribed per drug grouping by bnf_name
quantity_cambridge=pd.DataFrame(prescribing_cambridge.groupby(prescribing_cambridge.bnf_name).appl
y(lambda subf: subf['quantity'].sum()))

# Rename the column
quantity_cambridge.columns=['total_quantity_prescribed_per_drug']
# Reset the index
quantity_cambridge.reset_index(inplace=True)

# Sort the data according to the total quantity prescribed
quantity_cambridge_sorted=quantity_cambridge.sort_values('total_quantity_prescribed_per_drug', axi
s=0, ascending=False, kind='quicksort', na_position='last')
# Select the top 10 most frequent drugs prescribed
top_10_cambridge=quantity_cambridge_sorted.head(10)
# Reset the index
top_10_cambridge=top_10_cambridge.reset_index(drop=True)

# The top 10 most frequent drugs prescribed
top_10_cambridge
```

Out[142]:

	bnf_name	total_quantity_prescribed_per_drug
0	Fortisip Compact_Liq (8 Flav)	910125
1	Nutrison Pack_Energy	651324
2	Paracet_Tab 500mg	545299
3	Fortisip Bottle_Liq (8 Flav)	482936
4	Dermol 500_Lot	432000
5	Omeprazole_Cap E/C 20mg	429367
6	Nutrison Pack_Energy M/Fibre	409716
7	Lactulose_Soln 3.1g-3.7g/5ml	405920
8	Metformin HCl_Tab 500mg	303405
9	Fortijuce_Liq (7 Flav)	280600

- Q2.4 The top 10 most frequent drugs prescribed across all GP practices located in city of Cambridge:

Rank	Drug	Total quantity prescribed
1	Fortisip Compact_Liq (8 Flav)	910125
2	Nutrison Pack_Energy	651324
3	Paracet_Tab 500mg	545299
4	Fortisip Bottle_Liq (8 Flav)	482936
5	Dermol 500_Lot	432000
6	Omeprazole_Cap E/C 20mg	429367
7	Nutrison Pack_Energy M/Fibre	409716
8	Lactulose_Soln 3.1g-3.7g/5ml	405920
9	Metformin HCl_Tab 500mg	303405
10	Fortijuce_Liq (7 Flav)	280600

2.5 the bottom 10 less frequent drugs prescribed

In [144]:

```
# The bottom 10 most frequent drugs prescribed
bottom_10_cambridge=quantity_cambridge_sorted.tail(10)
# Reset the index
bottom_10_cambridge = bottom_10_cambridge.reset_index(drop=True)

# the bottom 10 less frequent drugs prescribed
bottom_10_cambridge
```

Out[144]:

	bnf_name	total_quantity_prescribed_per_drug
0	Gardasil 9_Vac 0.5ml Pfs	1
1	Optiflo G Cath Maint Soln 100ml	1
2	Acti-Fast 2-Way Stch 7.5cmx1m (Blue) Stk	1
3	Coloplast_Brava Skin Barrier Crm 60ml	1
4	Limb Seal-Tight Adult Foot/Ankle Wound C	1
5	Hydrocort/Lido HCl_Spy 0.2%/1% 30ml	1
6	Opus_DeoGel Deodorising & Lubricating Ge	1
7	Coloplast_Brava Belt (For Sensura Mio) S	1
8	Loceryl Curanail_Medic Nail Lacquer 3ml	1
9	Picato_Gel 500mcg/g	0

Similarly, it can be observed that the total quantity of more than 10 drugs are equally small. To identify the least frequent drugs prescribed:

In [145]:
```
# Select the drugs, whose total number of prescription is 0 or 1
bottom_10_cambridge_update = quantity_cambridge_sorted[quantity_cambridge_sorted.total_quantity_pr
escribed_per_drug<=1]
# Reset the index
bottom_10_cambridge_update = bottom_10_cambridge_update.reset_index(drop=True)

# The least frequent drugs prescribed
bottom_10_cambridge_update.tail(10)
```

Out[145]:

	bnf_name	total_quantity_prescribed_per_drug
172	Gardasil 9_Vac 0.5ml Pfs	1
173	Optiflo G Cath Maint Soln 100ml	1
174	Acti-Fast 2-Way Stch 7.5cmx1m (Blue) Stk	1
175	Coloplast_Brava Skin Barrier Crm 60ml	1
176	Limb Seal-Tight Adult Foot/Ankle Wound C	1
177	Hydrocort/Lido HCl_Spy 0.2%/1% 30ml	1
178	Opus_DeoGel Deodorising & Lubricating Ge	1
179	Coloplast_Brava Belt (For Sensura Mio) S	1
180	Loceryl Curanail_Medic Nail Lacquer 3ml	1
181	Picato_Gel 500mcg/g	0

In [148]:
```
# Count the number of the drugs
bottom_10_cambridge_update.bnf_name.count()
```

Out[148]: 182

- Q2.5 In this dataset, the least frequent drug prescribed is Picato_Gel 500mcg/g. There are 181 drugs which are prescribed only once.

2.6 Discuss and compare your findings with the answers for London in question 1 above using descriptive statistics.

2.6.1 Discuss and compare total number of patients registered, prescriptions and total actual cost of these prescriptions in city of Cambridge to London

- Total number of patients registered, prescriptions and total actual cost are not comparable between two areas because of different size of area and thus different total number of practices.
- Compare number of patients per practice, number of prescriptions per practice and actual cost per drug instead using statistical criteria mean, standard deviation, maximum value and minimum value.

In [460]:

```
n1=patient_london.practice_code.count()
n2=patient_london.practice_code.count()

# Compare number of patients per practice
x=patient_london.number_of_patients.copy(deep=True)
x=x/n1
y=patient_cambridge.number_of_patients.copy(deep=True)
y=y/n2
summary_patients=pd.DataFrame(
    {'London':[np.mean(x),np.std(x),np.max(x),np.min(x)],
    'City of Cambridge':[np.mean(y),np.std(y),np.max(y),np.min(y)]},
    index=['mean','std','max','min'])
summary_patients
```

Out[460]:

	City of Cambridge	London
mean	13.025325	10.164105
std	8.149170	6.521504
max	43.507792	93.801299
min	0.737662	0.010390

In [462]:

```
# Compare number of prescriptions per practice
x=prescribing_london.quantity.copy(deep=True)
x=x/n1
y=prescribing_cambridge.quantity.copy(deep=True)
y=y/n2
summary_prescription=pd.DataFrame(
    {'London':[np.mean(x),np.std(x),np.max(x),np.min(x)],
    'City of Cambridge':[np.mean(y),np.std(y),np.max(y),np.min(y)]},
    index=['mean','std','max','min'])
summary_prescription
```

Out[462]:

	City of Cambridge	London
mean	0.813017	0.820878
std	3.986695	4.621247
max	206.587013	1272.727273
min	0.000000	0.000000

In [463]:
```
# Compare actual cost per drug
x=prescribing_london.act_cost
y=prescribing_cambridge.act_cost
summary_act_cost=pd.DataFrame(
    {'London':[np.mean(x),np.std(x),np.max(x),np.min(x)],
    'City of Cambridge':[np.mean(y),np.std(y),np.max(y),np.min(y)]},
    index=['mean','std','max','min'])
summary_act_cost
```

Out[463]:

	City of Cambridge	London
mean	60.309027	53.872358
std	157.543906	135.574505
max	8099.100000	13744.790000
min	0.000000	0.090000

- Q2.6.1 City of Cambridge on average have 1) more patients per practice, 2) less prescriptions per practice and 3) higher actual cost per drug, compared to London.

2.6.2 Discuss and compare the top 10 most frequent drugs prescribed and the bottom 10 less frequent drugs prescribed

Cambridge	--	--	--	London	--	--
Rank	Drug	Total quantity prescribed		Rank	Drug	Total quantity prescribed
1	Fortisip Compact_Liq (8 Flav)	910125		1	Ensure Plus_Milkshake Style Liq (9 Flav)	17618168
2	Nutrison Pack_Energy	651324		2	Metformin HCl_Tab 500mg	12067995
3	Paracet_Tab 500mg	545299		3	Fortisip Bottle_Liq (8 Flav)	10435984
4	Fortisip Bottle_Liq (8 Flav)	482936		4	Lactulose_Soln 3.1g-3.7g/5ml	9573152
5	Dermol 500_Lot	432000		5	Paracet_Tab 500mg	7953529
6	Omeprazole_Cap E/C 20mg	429367		6	Dermol 500_Lot	6926000
7	Nutrison Pack_Energy M/Fibre	409716		7	Ensure Compact_Liq (4 Flav)	6887822
8	Lactulose_Soln 3.1g-3.7g/5ml	405920		8	Fresubin 2kcal_Drink (6 Flav)	6723152
9	Metformin HCl_Tab 500mg	303405		9	Fortisip Compact_Liq (8 Flav)	5610000
10	Fortijuce_Liq (7 Flav)	280600		10	Omeprazole_Cap E/C 20mg	4834655

- Q2.6.2

1) The frequency of drugs prescribed in city of Cambridge and London is similar. Though slightly different ranking, most drugs are among top 10 in both areas: Fortisip Compact_Liq (8 Flav), Paracet_Tab 500mg, Fortisip Bottle_Liq (8 Flav), Dermol 500_Lot , Omeprazole_Cap E/C 20mg, Omeprazole_Cap E/C 20mg, Lactulose_Soln 3.1g-3.7g/5ml, Metformin HCl_Tab 500mg. 2) Patients in city of Cambridge tend to use more Nutrison but less Ensure and Fresubin.

3. Describe total number of prescriptions and their total actual cost across all practices for selected drugs

3.1 Cardiovascular disease (British National Formulary chapter 2)

Identify drugs related to Cardiovascular disease.

The selection rule is: include the drug if its bnf code starts with '02', which refer to British National Formulary chapter 2.

In [149]:
```
# Identify drugs related to Cardiovascular disease
cardiovascular_bnf_code_regex='02'
prescribing_cardiovascular=prescribing[prescribing.bnf_code.str.match(cardiovascular_bnf_code_rege
x)]
prescribing_cardiovascular.head()
```

Out[149]:

	sha	pct	practice	bnf_code	bnf_name	items	nic	act_cost	quantity	period
28	Q44	RTV	Y05294	0204000R0AAAHAH	Propranolol HCl_Tab 10mg	4	7.12	6.65	224	201804
29	Q44	RTV	Y05294	0204000R0AAAJAJ	Propranolol HCl_Tab 40mg	3	1.35	1.59	42	201804
337	Q44	RXA	Y00327	0202020D0AAAEAE	Bumetanide_Tab 1mg	1	0.26	0.35	6	201804
338	Q44	RXA	Y00327	0202020L0AABBBB	Furosemide_Tab 20mg	1	0.13	0.23	10	201804
339	Q44	RXA	Y00327	0202020L0AABDBD	Furosemide_Tab 40mg	1	0.17	0.27	14	201804

3.1.1 Total number of prescriptions across all practices for drugs related to cardiovascular

In [152]:
```
# Calculate the total number of prescriptions across all practices for drugs related to cardiovasc
ular
total_number_of_prescriptions_cardiovascular = prescribing_cardiovascular.quantity.sum()
total_number_of_prescriptions_cardiovascular
```

Out[152]: 933262147

- Q3.1.1 The total number of prescriptions across all practices for drugs related to cardiovascular is 933,262,147

3.1.2 Total actual cost across all practices for drugs related to cardiovascular

In [153]:
```
# Calculate total actual cost across all practices for drugs related to cardiovascular
total_act_cost_cardiovascular=prescribing_cardiovascular.act_cost.sum()
total_act_cost_cardiovascular
```

Out[153]: 90193834.01999994

- Q3.1.2 The total actual cost across all practices for drugs related to cardiovascular is 90,193,834

3.2 Antidepressants disease (British National Formulary chapter 4.3)

Identify drugs related to Antidepressants disease.

The selection rule is: include the drug if its bnf code starts with '0403', which refer to British National Formulary chapter 4.3.

In [155]:
```
# Identify drugs related to Antidepressants disease
antidepressants_bnf_code_regex='0403'
prescribing_antidepressants=prescribing[prescribing.bnf_code.str.match(antidepressants_bnf_code_re
gex)]
prescribing_antidepressants.head()
```

Out[155]:

	sha	pct	practice	bnf_code	bnf_name	items	nic	act_cost	quantity	period
9	Q44	RTV	Y04937	0403010X0AAAAAA	Trazodone HCl_Cap 50mg	1	1.19	1.22	14	201804
10	Q44	RTV	Y04937	0403030D0AAAAAA	Citalopram Hydrob_Tab 20mg	1	1.17	1.20	14	201804
11	Q44	RTV	Y04937	0403030D0AAABAB	Citalopram Hydrob_Tab 10mg	1	0.76	0.82	14	201804
12	Q44	RTV	Y04937	0403030P0AAAGAG	Paroxetine HCl_Oral Soln 10mg/5ml S/F	1	15.99	14.94	263	201804
13	Q44	RTV	Y04937	0403030P0AAAKAK	Paroxetine HCl_Tab 10mg	1	16.50	15.41	49	201804

3.2.1 total number of prescriptions across all practices for drugs related to antidepressants

In [156]:
```
# Calculate the total number of prescriptions across all practices for drugs related to antidepres
sants
total_number_of_prescriptions_antidepressants = prescribing_antidepressants.quantity.sum()
total_number_of_prescriptions_antidepressants
```

Out[156]: 214223401

- Q3.2.1 The total number of prescriptions across all practices for drugs related to antidepressants is 214,223,401

3.2.2 total actual cost across all practices for drugs related to antidepressants

In [157]:
```
# Calculate total actual cost across all practices for drugs related to antidepressants
total_act_cost_antidepressants=prescribing_antidepressants.act_cost.sum()
total_act_cost_antidepressants
```

Out[157]: 16853470.86

- Q3.2.2 The total actual cost across all practices for drugs related to antidepressants is 16,853,471

4. Describe the total spending and the relative costs per patient across all practices for the month of April 2018:

4.1 Visualize the monthly total spending per registered patients using a scatterplot and provide a trend line

In [158]:
```
# Link dataframe 'patient' and 'practice' matching by practice code to identify number of patients registered at each practice
patient_practice = pd.merge(practice, patient[['code', 'number_of_patients']], left_on='practice_code' , right_on='code')
patient_practice.head()
```

Out[158]:

	timePeriod	practice_code	practice_name	practice_organization	street	city	
0	201804	A81001	THE DENSHAM SURGERY	THE HEALTH CENTRE	LAWSON STREET	STOCKTON-ON-TEES	C
1	201804	A81002	QUEENS PARK MEDICAL CENTRE	QUEENS PARK MEDICAL CTR	FARRER STREET	STOCKTON ON TEES	C
2	201804	A81004	BLUEBELL MEDICAL CENTRE	TRIMDON AVENUE	ACKLAM	MIDDLESBROUGH	
3	201804	A81005	SPRINGWOOD SURGERY	SPRINGWOOD SURGERY	RECTORY LANE	GUISBOROUGH	
4	201804	A81006	TENNANT STREET MEDICAL PRACTICE	TENNANT ST MEDICAL PRACT	TENNANT STREET	STOCKTON-ON-TEES	C

In [159]:
```
# Calculate total actual cost per Practice grouping by practice code
act_cost_practice = pd.DataFrame(prescribing.groupby(prescribing.practice).apply(lambda subf: subf
['act_cost'].sum()))
# Rename the column
act_cost_practice.columns=['total_actual_cost']
# Reset the index
act_cost_practice.reset_index(inplace=True)
act_cost_practice.head()
```

Out[159]:

	practice	total_actual_cost
0	A81001	52194.63
1	A81002	268607.26
2	A81004	139115.40
3	A81005	102914.06
4	A81006	183226.79

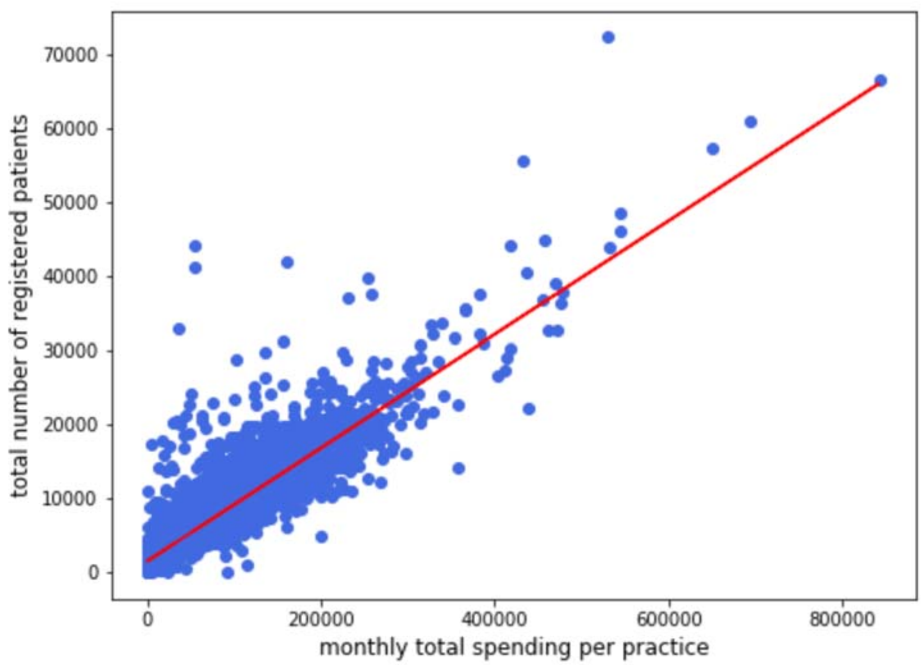
In [160]:
```
# Link dataframe 'act_cost_practice' and 'patient_practice' matching by practice code to link tota
l spending and total number of patients for each practice
patient_total_spending = pd.merge(act_cost_practice, patient_practice[['code', 'number_of_patients
']], left_on='practice' , right_on='code')
patient_total_spending.head()
```

Out[160]:

	practice	total_actual_cost	code	number_of_patients
0	A81001	52194.63	A81001	4086
1	A81002	268607.26	A81002	19906
2	A81004	139115.40	A81004	10165
3	A81005	102914.06	A81005	8016
4	A81006	183226.79	A81006	14497

In [161]:
```
# Visualize the monthly total spending per registered patients using a scatterplot and provide a t
rend line

fig=plt.figure(figsize=(8,6))
ax=fig.add_subplot(111)

x=patient_total_spending.total_actual_cost
y=patient_total_spending.number_of_patients

# plot those data points
ax.scatter(x,y,color='royalblue')

# Fit a polynomial of degree deg to points (x, y). Returns a vector of coefficients p that minimis
es the squared error.
fit=np.polyfit(x,y,deg=1)
ax.plot(x, fit[0] * x + fit[1], color='red')

# Set title and labels
ax.set_title='Scatter plot: monthly total spending / registered patients'
ax.set_xlabel("monthly total spending per practice",fontsize=12)
ax.set_ylabel("total number of registered patients",fontsize=12)
```

Out[161]: Text(0,0.5,'total number of registered patients')



Outlier detection

1) Reaonable extreme values

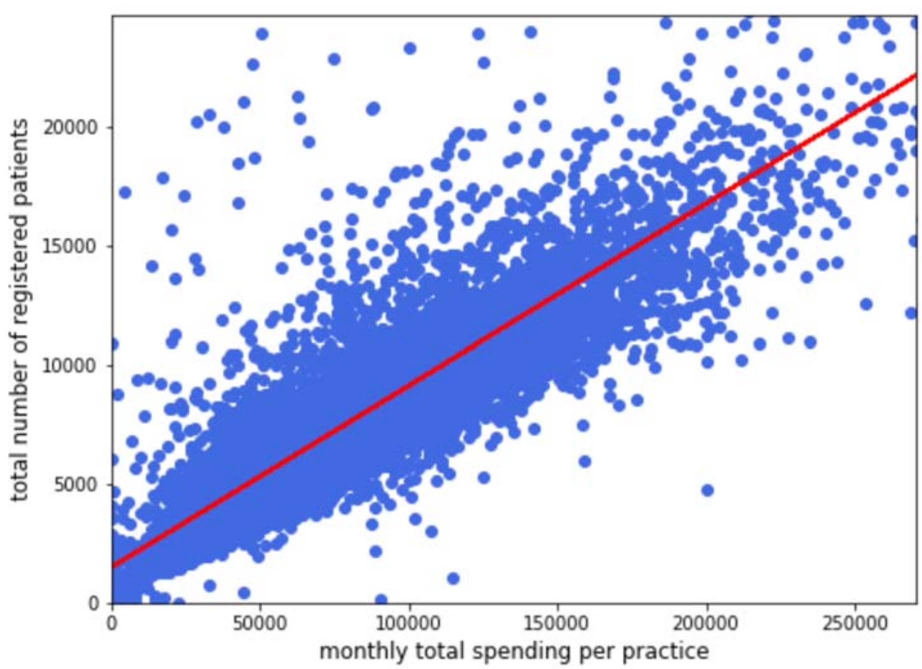
- It can be observed from the scatter plot that there are data points with extremely large values.
- As explained in part 0.3, they are reasonable data because some practice are of huge size.
- However, they would cause other data points to squeeze on the figure, which is not suitable for presentation.
- Therefore, we need to modify the max-value of x and y-axis, so that the outliers are not shown.
- They should not be excluded from the initial dataset

2) Unreasonalbe extreme values - Outliers

- It can also be observed from the scatter plot that there are data points far away from the trend line.
- They would to to some extent affect the performance of the trend line fitted, because of their unreasonable extreme leverage.
- Also, as explained in part 0.3, they would largely affect the mean values when calculating relative costs per patient.
- Therefore, the outliers should be excluded from the initial dataset. In consideration of efficiency, they are only manipulated in part 4.2.

In [258]:
```
# Visualize the monthly total spending per registered patients using a scatterplot and provide a t
rend line, do not show extreme values in x and y-axis

# Plot those data points
fig=plt.figure(figsize=(8,6))
ax=fig.add_subplot(111)

x=cost_per_patient.total_actual_cost
y=cost_per_patient.number_of_patients

ax.scatter(x,y,color='royalblue')

fit=np.polyfit(x,y,deg=1)
ax.plot(x, fit[0] * x + fit[1], color='red')

ax.set_title='Scatter plot: monthly total spending / registered patients'
ax.set_xlabel("monthly total spending per practice",fontsize=12)
ax.set_ylabel("total number of registered patients",fontsize=12)

# Modify the max-value of x and y-axis
max_x = floor(cost_per_patient.total_actual_cost.quantile(.99))
max_y = floor(cost_per_patient.number_of_patients.quantile(.99))
ax.set_xlim(0, max_x)
ax.set_ylim(0, max_y)
```

Out[258]: (0, 24766.0)



In [259]:
```
# Print the regression model of the dataset
beta = str(round((1/fit[0]),3))
alpha = str(round((-fit[1]/fit[0]),3))
'monthly total spending per practice = ' + beta + ' * total number of registered patients ' + alph
a
```

Out[259]: 'monthly total spending per practice = 13.068 * total number of registered patients -19413.28'

- Q4.1 It can be observed from the scatter plot that total number of patients and total spending are positively associated across all GP practices. The regression model is:

```
monthly total spending per practice = 13.068 * total number of registered patients -19413.28
```

For every one patient registered, the total spending increase by 13.068 pounds.

Outlier manipulation

1) To exclude outliers, first calculate the relative costs per patient of each practice.

2) Exclude outliers according to the rules of generating a box plot.

3) Visualize the result of excluding outliers with box plot.

In [261]:
```
# Calculate the relative costs per patient of each practice
cost_per_patient = patient_total_spending
cost_per_patient['cost_per_patient'] = cost_per_patient['total_actual_cost'] / cost_per_patient['n
umber_of_patients']
cost_per_patient.head()
```

Out[261]:

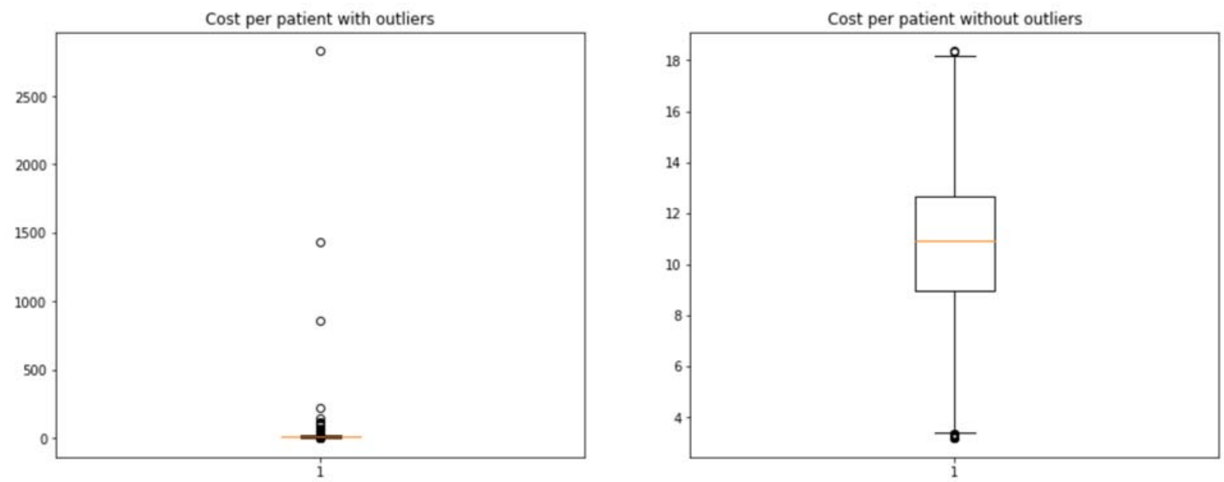
	practice	total_actual_cost	code	number_of_patients	cost_per_patient
0	A81001	52194.63	A81001	4086	12.774016
1	A81002	268607.26	A81002	19906	13.493784
2	A81004	139115.40	A81004	10165	13.685726
3	A81005	102914.06	A81005	8016	12.838580
4	A81006	183226.79	A81006	14497	12.638945

In [264]:
```
# Calculate the quantiles
[Q1,Q3]=cost_per_patient.cost_per_patient.quantile([0.25,0.75])
# Calculate interquartile range
IQR = Q3 - Q1
# Exclude outliers
cost_per_patient_cleaned = cost_per_patient[(cost_per_patient.cost_per_patient>=(Q1-1.5*IQR))&(cos
t_per_patient.cost_per_patient<=(Q3+1.5*IQR))]
cost_per_patient_cleaned.head()
```

Out[264]:

	practice	total_actual_cost	code	number_of_patients	cost_per_patient
0	A81001	52194.63	A81001	4086	12.774016
1	A81002	268607.26	A81002	19906	13.493784
2	A81004	139115.40	A81004	10165	13.685726
3	A81005	102914.06	A81005	8016	12.838580
4	A81006	183226.79	A81006	14497	12.638945

In [265]:
```
# Visualize the result of excluding outliers with box plot

fig = plt.figure(figsize=(16,6))

# Plot a box plot of cost per patient with outliers
fig1 = plt.subplot(121)
x1 = cost_per_patient.cost_per_patient.values
plt.boxplot(x1)
plt.title('Cost per patient with outliers')

# Plot a box plot of cost per patient without outliers
fig2 = plt.subplot(122)
x2 = cost_per_patient_cleaned.cost_per_patient
plt.boxplot(x2)
plt.title('Cost per patient without outliers')

plt.show()
plt.close()
```

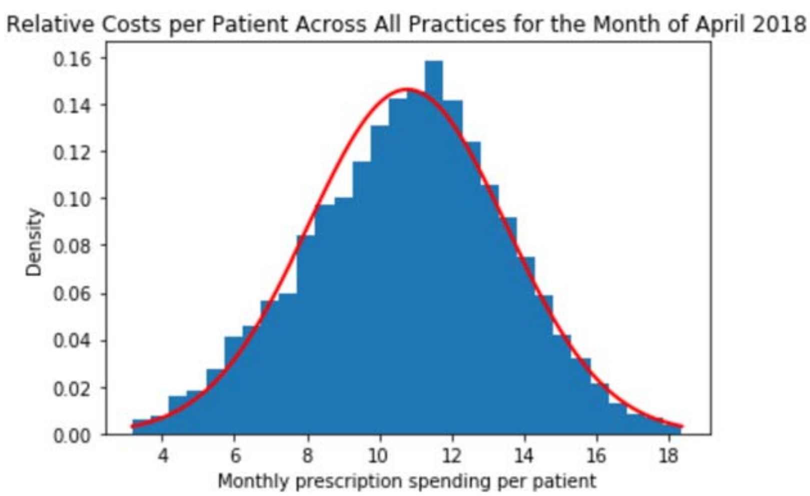


4.2 Generate a histogram for relative spending for all practices and fit a Gaussian(normal) curve

In [266]:

```
# Generate a histogram for relative spending for all practices
x = cost_per_patient_cleaned.cost_per_patient.values
plt.hist(x, bins=30, normed=True)

# Fit a Gaussian(normal) curve
import matplotlib.mlab as mlab

min_x=min(x)
max_x=max(x)
mu = np.mean(x)
sigma = np.std(x)
x2=np.linspace(min_x, max_x,100)
plt.plot(x2, mlab.normpdf(x2,mu,sigma), 'r', linewidth=2)

plt.xlabel("Monthly prescription spending per patient")
plt.ylabel("Density")
plt.title("Relative Costs per Patient Across All Practices for the Month of April 2018")

plt.show()
plt.close()
```

```
D:\Anaconda\lib\site-packages\ipykernel_launcher.py:13: MatplotlibDeprecationWarning: scipy.stats
.norm.pdf
  del sys.path[0]
```



In [267]:

```
# Print mean of relative cost per patient
round(mu,2)
```

Out[267]: 10.78

- Q1.5 It can be observed from the histogram and Gaussian curve that relative cost per patient is only slightly negative skewed. Patients on average spend 10.78 pounds in practices for the month of April 2018.

Assignment B - WHO Mortality Database

Overview of Assignment B

1) Assignment B uses data from WHO Mortality Database to analyse causes of death in different countries.

2) There are mainly 3 files used in this session and are read into 3 DataFrames named 'country_code', 'population' and 'mortality':

- country_codes: country codes and names
- population: population (at all ages and at each age group) and live births
- mortality: cause of death according to ICD-10 (either with 3 characters or 4 characters ICD 10 codes) and number of deaths (at all ages and at each age group)

3) There are 4 criteria used to identify the subsets of interest: Country, Casue of death, Year and Age group, to address 4 kinds of problem: Population and number of death, distribution of deaths by age groups, top casuses of death, top age groups dying, as well as comparing two countries with a combination of analysis above.

Question	**Country**	**Cause of Deaths**	**Year**	**Age Group**	**Problem**
1	Iceland / Italy / New Zealand	All causes	2010	All ages	Population & Total number of deaths
2	Italy	All causes	All years	Age groups	Distribution of deaths by age groups
3	Italy	Neoplasm	All years	All ages	Top causes of death
4	Australia	Neoplasm	2010	Age groups	Top age groups dying
5	Italy & Australia	Neoplasm	2010	All ages / Age groups	Comparison

- The matching variable 'Country' is identified by country code, looked up in 'country_code'.
- Cause of deaths is identified by 3 characters ICD 10 codes (coverting 4 characters codes to 3 characters ones) according to WHO web site 'https://icd.who.int/browse10/2016/en#/C34.9 (https://icd.who.int/browse10/2016/en#/C34.9)'
- Pop1/Deaths1 refers to all ages, while Pop2-26/Deaths2-26 refers to each age group, according to the documentation of WHO mortality database

4) Data preparation include reading in files, analysing missing values and outliers, as well as summarizing data. These process are conducted both at the beginning and later in in the assignment. Data prepareation enables reliable results based on quality dataset.

5) The results of analysis are interpreted using a combination of narrative, tables, figures, and descriptive statistics

0. Data preparation

0.1 Read in files to pandas dataframes

In [271]:

```
# Read in "Country codes" look up file which contains identifier codes

# Create custom column names and read in the country codes data file using the column names as the
header.
filename = path + 'country_codes.csv'
cols = ['Country', 'Name']
country_codes = pd.read_csv(filename, sep=',',header=None, names=cols,index_col=False, skiprows=1)
.rename(columns=lambda x: x.strip())

# Explore the data using built-in methods
country_codes.head()
```

Out[271]:

	Country	Name
0	1010	Algeria
1	1020	Angola
2	1025	Benin
3	1030	Botswana
4	1035	Burkina Faso

In [272]:

```
# Read in "Population and live births" file which contains information on the population of each c
ountry

filename = path + 'pop.csv'
cols = ['Country', 'Admin1', 'SubDiv', 'Year', 'Sex', 'Frmat', 'Pop1', 'Pop2', 'Pop3', 'Pop4', 'Po
p5', 'Pop6', 'Pop7', 'Pop8', 'Pop9', 'Pop10', 'Pop11', 'Pop12', 'Pop13', 'Pop14', 'Pop15', 'Pop16'
, 'Pop17', 'Pop18', 'Pop19', 'Pop20', 'Pop21', 'Pop22', 'Pop23', 'Pop24', 'Pop25', 'Pop26', 'Lb']
population = pd.read_csv(filename, sep=',',header=None, names=cols,index_col=False, skiprows=1).re
name(columns=lambda x: x.strip())

population.head()
```

Out[272]:

	Country	Admin1	SubDiv	Year	Sex	Frmat	Pop1	Pop2	Pop3	Pop4	...	Pop18	Po
0	1060	NaN	NaN	1980	1	7	137100.0	3400.0	15800.0	NaN	...	NaN	530(
1	1060	NaN	NaN	1980	2	7	159000.0	4000.0	18400.0	NaN	...	NaN	620(
2	1125	NaN	NaN	1955	1	2	5051500.0	150300.0	543400.0	NaN	...	110200.0	511(
3	1125	NaN	NaN	1955	2	2	5049400.0	145200.0	551000.0	NaN	...	122100.0	511(
4	1125	NaN	NaN	1956	1	2	5353700.0	158700.0	576600.0	NaN	...	116900.0	541(

5 rows × 33 columns

In [273]:
```
# Read in "Morticd10" files  which report the cause of death using the 10th revision of the Intern
ational Classification of Diseases (ICD-10)
filename = path + 'Morticd10_part1.csv'
cols = ['Country', 'Admin1', 'SubDiv', 'Year', 'List', 'Cause', 'Sex', 'Frmat', 'IM_Frmat', 'Death
s1', 'Deaths2', 'Deaths3', 'Deaths4', 'Deaths5', 'Deaths6', 'Deaths7', 'Deaths8', 'Deaths9', 'Deat
hs10', 'Deaths11', 'Deaths12', 'Deaths13', 'Deaths14', 'Deaths15', 'Deaths16', 'Deaths17', 'Deaths
18', 'Deaths19', 'Deaths20', 'Deaths21', 'Deaths22', 'Deaths23', 'Deaths24', 'Deaths25', 'Deaths26
', 'IM_Deaths1', 'IM_Deaths2', 'IM_Deaths3', 'IM_Deaths4']

# According to the documentation, the fields “Admin1”, “Subdiv”, “List”, “Cause”, “Frmat
” and “IM_Frmat” should be treated as characters.  The other fields can be treated as numerical
variables.
mortality_1 = pd.read_csv(filename, sep=',',header=None, names=cols,index_col=False, skiprows=1, d
type = {'Admin1': object, 'SubDiv': object, 'List': object, 'Cause': object, 'Frmat': object, 'IM_
Frmat': object}).rename(columns=lambda x: x.strip())

mortality_1.head()
```

Out[273]:

	Country	Admin1	SubDiv	Year	List	Cause	Sex	Frmat	IM_Frmat	Deaths1	...	Deaths21	Deaths2
0	1400	NaN	NaN	2001	101	1000	1	07	08	332	...	95.0	NaN
1	1400	NaN	NaN	2001	101	1000	2	07	08	222	...	112.0	NaN
2	1400	NaN	NaN	2001	101	1001	1	07	08	24	...	5.0	NaN
3	1400	NaN	NaN	2001	101	1001	2	07	08	14	...	6.0	NaN
4	1400	NaN	NaN	2001	101	1002	1	07	08	0	...	0.0	NaN

5 rows × 39 columns

In [274]:
```
filename = path + 'Morticd10_part2.csv'
mortality_2 = pd.read_csv(filename, sep=',',header=None, names=cols,index_col=False, skiprows=1, d
type = {'Admin1': object, 'SubDiv': object, 'List': object, 'Cause': object, 'Frmat': object, 'IM_
Frmat': object}).rename(columns=lambda x: x.strip())
mortality_2.head()
```

Out[274]:

	Country	Admin1	SubDiv	Year	List	Cause	Sex	Frmat	IM_Frmat	Deaths1	...	Deaths21	Deaths2
0	1400	NaN	NaN	2005	101	1000	1	07	08	386	...	136.0	NaN
1	1400	NaN	NaN	2005	101	1000	2	07	08	287	...	163.0	NaN
2	1400	NaN	NaN	2005	101	1001	1	07	08	29	...	13.0	NaN
3	1400	NaN	NaN	2005	101	1001	2	07	08	21	...	16.0	NaN
4	1400	NaN	NaN	2005	101	1002	1	07	08	0	...	0.0	NaN

5 rows × 39 columns

In [275]:
```
# Merge the two mortality dataframes into one dataframe
mortality = pd.concat([mortality_1, mortality_2])

mortality.head()
```

Out[275]:

	Country	Admin1	SubDiv	Year	List	Cause	Sex	Frmat	IM_Frmat	Deaths1	...	Deaths21	Deaths2
0	1400	NaN	NaN	2001	101	1000	1	07	08	332	...	95.0	NaN
1	1400	NaN	NaN	2001	101	1000	2	07	08	222	...	112.0	NaN
2	1400	NaN	NaN	2001	101	1001	1	07	08	24	...	5.0	NaN
3	1400	NaN	NaN	2001	101	1001	2	07	08	14	...	6.0	NaN
4	1400	NaN	NaN	2001	101	1002	1	07	08	0	...	0.0	NaN

5 rows × 39 columns

0.2 Check out the missing values

In [279]:
```
# The missing value are automatically coded as NaN. Count non-NA/null values of each object
country_codes.count(),country_codes.shape
```

Out[279]:
```
(Country    227
 Name       227
 dtype: int64, (227, 2))
```

In [281]:
```
population.count(),population.shape
```

Out[281]:
```
(Country    9349
 Admin1       82
 SubDiv      138
 Year       9349
 Sex        9349
 Frmat      9349
 Pop1       9349
 Pop2       9213
 Pop3       9213
 Pop4       5152
 Pop5       5152
 Pop6       5152
 Pop7       9213
 Pop8       9195
 Pop9       9213
 Pop10      9195
 Pop11      9213
 Pop12      9195
 Pop13      9213
 Pop14      9195
 Pop15      9213
 Pop16      9195
 Pop17      9213
 Pop18      9195
 Pop19      9213
 Pop20      9151
 Pop21      9057
 Pop22      8197
 Pop23      8197
 Pop24      1148
 Pop25      1148
 Pop26      9195
 Lb         9125
 dtype: int64, (9349, 33))
```

```
In  [282]: mortality.count(), mortality.shape
```

```
Out[282]: (Country       3587860
           Admin1          84173
           SubDiv           2707
           Year          3587860
           List          3587860
           Cause         3587860
           Sex           3587860
           Frmat         3587860
           IM_Frmat      3587860
           Deaths1       3587860
           Deaths2       3585618
           Deaths3       3585618
           Deaths4       3420612
           Deaths5       3420612
           Deaths6       3420612
           Deaths7       3585618
           Deaths8       3582633
           Deaths9       3585618
           Deaths10      3582633
           Deaths11      3585618
           Deaths12      3582633
           Deaths13      3585618
           Deaths14      3582633
           Deaths15      3585618
           Deaths16      3582633
           Deaths17      3585618
           Deaths18      3582633
           Deaths19      3585618
           Deaths20      3582309
           Deaths21      3585294
           Deaths22      3574442
           Deaths23      3574442
           Deaths24      3109293
           Deaths25      3109293
           Deaths26      3585618
           IM_Deaths1    3585617
           IM_Deaths2    2779471
           IM_Deaths3    2868691
           IM_Deaths4    2868691
           dtype: int64, (3587860, 39))
```

Missing value analysis:

- There is no missing value in column 'Country' of all the three dataframes, which represents the unique country code of each country. Therefore, country code is a matching variable of high quality for linking these dataframes.
- There is no missing value in columns 'Pop1' and 'Deaths1'. Therefore, the calculation of population and number of deaths across all ages wouldn't be affected by missing values.
- There are many missing values in columns 'Pop2' to 'Pop26'. Therefore, problem of missing values should be taken into account while analysing population of each age group.
- There are a few missing values in columns 'Deaths2' to 'Deaths26', it could be because that there is no deaths for certain disease in that country, year and age group, which are acceptable.
- Missing value in columns 'Admin1'and 'Subdiv' mean data reported refer to the country, which are reasonable.

1. What was the population and the total number of deaths (from all causes, all ages) in 2010 for: 1) Iceland 2) Italy 3) New Zealand

In [288]:
```
# Look up the country code for Iceland
country_name='Iceland'
country_codes_Iceland=country_codes['Country'][country_codes.Name==country_name].values[0]
country_codes_Iceland
```

Out[288]: 4160

In [289]:
```
# Calculate the population in 2010 for Iceland

# The subset of population data is matched by the country code and the year of interest
population_Iceland_2010=population[(population.Country==country_codes_Iceland)&(population.Year==2
010)]
# Number of population (from each gender) is contained in the column 'Pop1'(Population at all ages
). Sum up the values to get whole population.
total_population_Iceland_2010=sum(population_Iceland_2010.Pop1)
total_population_Iceland_2010
```

Out[289]: 318041.0

In [290]:
```
# Calculate the total number of deaths (from all causes, all ages) in 2010 for Iceland

# The subset of mortality data is matched by the country code and the year of interest
mortality_Iceland_2010=mortality[(mortality.Country==country_codes_Iceland)&(mortality.Year==2010)
]
# Sum up the values of column 'Deaths1' wich contains number of death at all ages for each cause a
nd gender
total_mortality_Iceland_2010=sum(mortality_Iceland_2010.Deaths1)
total_mortality_Iceland_2010
```

Out[290]: 4038L

In [291]:
```
# Look up the country code for Italy
country_name='Italy'
country_codes_Italy=country_codes['Country'][country_codes.Name==country_name].values[0]
country_codes_Italy
```

Out[291]: 4180

In [292]:
```
# Calculate the population in 2010 for Italy
population_Italy_2010=population[(population.Country==country_codes_Italy)&(population.Year==2010)
]
total_population_Italy_2010=sum(population_Italy_2010.Pop1)
total_population_Italy_2010
```

Out[292]: 60483386.0

In [293]:
```
# Calculate the total number of deaths (from all causes, all ages) in 2010 for Italy
mortality_Italy_2010=mortality[(mortality.Country==country_codes_Italy)&(mortality.Year==2010)]
total_mortality_Italy_2010=sum(mortality_Italy_2010.Deaths1)
total_mortality_Italy_2010
```

Out[293]: 1169230L

In [294]:
```
# Look up the country code for Iceland
country_name='New Zealand'
country_codes_New_Zealand=country_codes['Country'][country_codes.Name==country_name].values[0]
country_codes_New_Zealand
```

Out[294]: 5150

In [295]:
```
# Calculate the population in 2010 for Iceland
population_New_Zealand_2010=population[(population.Country==country_codes_New_Zealand)&(population
.Year==2010)]
total_population_New_Zealand_2010=sum(population_New_Zealand_2010.Pop1)
total_population_New_Zealand_2010
```

Out[295]: 4367360.0

In [296]:
```
# Calculate the total number of deaths (from all causes, all ages) in 2010 for Iceland
mortality_New_Zealand_2010=mortality[(mortality.Country==country_codes_New_Zealand)&(mortality.Yea
r==2010)]
total_mortality_New_Zealand_2010=sum(mortality_New_Zealand_2010.Deaths1)
total_mortality_New_Zealand_2010
```

Out[296]: 57298L

In [297]:
```
# Generate a table with the name of country, population and total number of deaths
population_mortality = pd.DataFrame(
    {'Country':['Iceland', 'Italy', 'New Zealand'],
     'Population':[total_population_Iceland_2010, total_population_Italy_2010, total_population_Ne
w_Zealand_2010],
     'Total Number of Deaths':[total_mortality_Iceland_2010, total_mortality_Italy_2010, total_mor
tality_New_Zealand_2010]})
population_mortality
```

Out[297]:

	Country	Population	Total Number of Deaths
0	Iceland	318041.0	4038
1	Italy	60483386.0	1169230
2	New Zealand	4367360.0	57298

- Q1 The population and the total number of deaths (from all causes, all ages) in 2010 for: 1) Iceland 2) Italy 3) New Zealand are:

Country	Population	Total Number of Deaths
Iceland	318041.0	4038
Italy	60483386.0	1169230
New Zealand	4367360.0	57298

2. What was the distribution of deaths (all causes, all years) by age group in Italy?

In [298]:

```
# Calculate total number of deaths (all causes, all years) of each age group in Italy

# The subset of mortality data (all causes, all years) is matched by the country code of Italy
# Select columns 'Deaths2' to 'Deaths26' which contains number of deaths of each age group for eac
h cause and gender
mortality_Italy = mortality[mortality.Country==country_codes_Italy][['Deaths2', 'Deaths3', 'Deaths
4', 'Deaths5', 'Deaths6', 'Deaths7', 'Deaths8', 'Deaths9', 'Deaths10', 'Deaths11', 'Deaths12', 'De
aths13', 'Deaths14', 'Deaths15', 'Deaths16', 'Deaths17', 'Deaths18', 'Deaths19', 'Deaths20', 'Deat
hs21', 'Deaths22', 'Deaths23', 'Deaths24', 'Deaths25', 'Deaths26']]
mortality_Italy.head()
```

Out[298]:

	Deaths2	Deaths3	Deaths4	Deaths5	Deaths6	Deaths7	Deaths8	Deaths9	Deaths10	Death
1053321	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1053322	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1053323	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1053324	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1053325	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 25 columns

In [303]:

```
# Sum up the values of each column to get total number of deaths of each age group
mortality_Italy_age_group=pd.DataFrame(mortality_Italy.apply(lambda x: x.sum())).copy(deep=True)

# Reset the index
mortality_Italy_age_group.reset_index(inplace=True)
# Rename the columns
mortality_Italy_age_group.columns=['Age_Group','Deaths']

mortality_Italy_age_group.head()
```

Out[303]:

	Age_Group	Deaths
0	Deaths2	48752.0
1	Deaths3	3262.0
2	Deaths4	2168.0
3	Deaths5	1826.0
4	Deaths6	1628.0

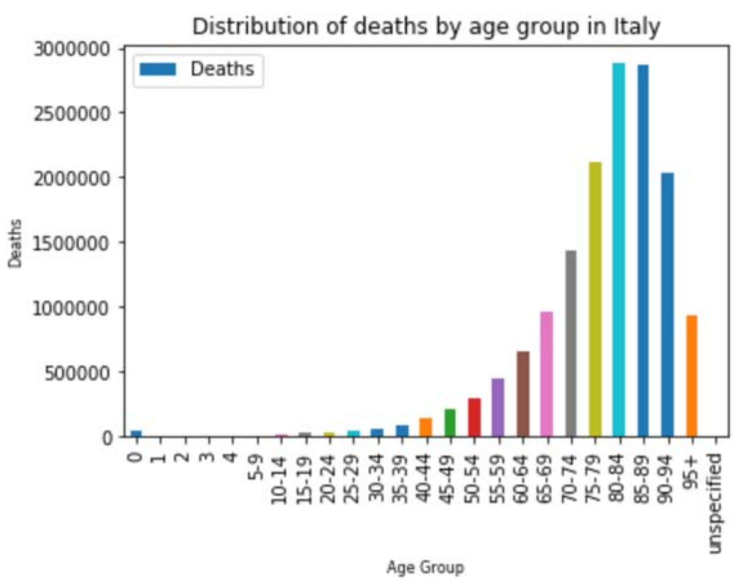
In [305]:
```
# Look up in documentation which age group each row represents
mortality_Italy_age_group['Age_Group']=['0', '1', '2', '3', '4', '5-9', '10-14', '15-19', '20-24',
'25-29', '30-34', '35-39', '40-44', '45-49', '50-54', '55-59', '60-64', '65-69', '70-74', '75-79',
'80-84', '85-89', '90-94', '95+', 'unspecified']
mortality_Italy_age_group.head()
```

Out[305]:

	Age_Group	Deaths
0	0	48752.0
1	1	3262.0
2	2	2168.0
3	3	1826.0
4	4	1628.0

In [306]:
```
# Visualise the results using a bar chart
ax=mortality_Italy_age_group[['Age_Group','Deaths']].plot(kind='bar', x='Age_Group', y='Deaths', t
itle='Distribution of deaths by age group in Italy', figsize=(6,4),legend=True, fontsize=10)

ax.set_xlabel("Age Group",fontsize=8)

ax.set_ylabel("Deaths",fontsize=8)
```

Out[306]: Text(0,0.5,'Deaths')



- Q2 It can be observed from the bar chart that total number of death for each age group increases rapidly with increase in age, and reaches the peak around 2,900,000 in age group 80-84. The decrease of number of death in older age groups may due to decrease of populaiton of that age group. We can refer to detailed numbers of death in the table (dataframe) printed above.

3. What were the top five causes of death (top five ICD-10 terms) in Italy across all years for the Neoplasm ICD10-category (C00-D48)?

Identify the regex-patterns of ICD-10 codes of Neoplasm

- According to the documentation, the ICD-10 codes can have either 3 or 4 digits. A cause with 4 digits (e.g.C349) is a subtype of the cause defined by the former 3 digits (i.e.C34)
- The most important disadvantage of ICD-10 is its fixed depth (a lot of classification go to the 10th term (e.g.C34.9) which is unspecified). It can also be computed in this dataset that the most prevalent subtypes of Neoplasm are those defined by 4-digit ICD-10 codes ending up with 9 (e.g.C349), which is 'unspecified'.
- The use of ‘unspecified’ and mixed use of 3- and 4- digit codes make it unclear to discover the real prevalence of each cause. Therefore, it is necessary to convert 4-digit codes into 3-digit ones, which together represent the sum of all deaths due to the base type of disease.

In [307]:

```
# The regex-patterns refer to ICD-10 codes C00-D48, including both 3- and 4- digit codes, to ident
ify all the Neoplasm categories

neoplasm_regex='C\d{2}|D[0-3]\d|D4[0-8]'
```

Discover the top five causes of death for Neoplasm

In [308]:

```
# The subset of mortality data is matched by the country code and the ICD-10 code
mortality_Italy_neoplasm=mortality[(mortality.Country==country_codes_Italy)&(mortality.Cause.str.m
atch(neoplasm_regex))]
mortality_Italy_neoplasm.head()
```

Out[308]:

	Country	Admin1	SubDiv	Year	List	Cause	Sex	Frmat	IM_Frmat	Deaths1	...	Deaths21	D
1053596	4180	NaN	NaN	2003	104	C000	1	00	01	2	...	0.0	1
1053597	4180	NaN	NaN	2003	104	C000	2	00	01	7	...	0.0	0
1053598	4180	NaN	NaN	2003	104	C001	1	00	01	21	...	3.0	7
1053599	4180	NaN	NaN	2003	104	C001	2	00	01	5	...	0.0	2
1053600	4180	NaN	NaN	2003	104	C009	1	00	01	24	...	3.0	8

5 rows × 39 columns

In [309]:

```
# Use deep copy in case the initial dataset would be changed when generating a new column
# To save memory, only select columns 'Cause' and 'Deaths1', which contain cause of death and numb
er of death at all ages
mortality_Italy_neoplasm_3digits=mortality_Italy_neoplasm[['Cause','Deaths1']].copy(deep=True)
mortality_Italy_neoplasm_3digits.head()
```

Out[309]:

	Cause	Deaths1
1053596	C000	2
1053597	C000	7
1053598	C001	21
1053599	C001	5
1053600	C009	24

In [310]:
```
# Convert 4-digit codes into 3-digit ones and store the new codes in column 'Cause_3digits'
mortality_Italy_neoplasm_3digits['Cause_3digits']=mortality_Italy_neoplasm_3digits['Cause'].apply(
lambda x: str(x)[0:3])
mortality_Italy_neoplasm_3digits.head()
```

Out[310]:

	Cause	Deaths1	Cause_3digits
1053596	C000	2	C00
1053597	C000	7	C00
1053598	C001	21	C00
1053599	C001	5	C00
1053600	C009	24	C00

In [311]:
```
# Sum up number of death of each age group grouping by the 3-digit ICD-10 codes, to get total numb
er of deaths due to each base type of disease.
total_mortality_Italy_neoplasm = pd.DataFrame(mortality_Italy_neoplasm_3digits.groupby(mortality_I
taly_neoplasm_3digits.Cause_3digits).apply(lambda subf: subf['Deaths1'].sum()))
# Rename the column
total_mortality_Italy_neoplasm.columns=['Total_Deaths']
# Reset the index
total_mortality_Italy_neoplasm.reset_index(inplace=True)

total_mortality_Italy_neoplasm.head()
```

Out[311]:

	Cause_3digits	Total_Deaths
0	C00	783
1	C01	1359
2	C02	5989
3	C03	329
4	C04	585

In [359]:
```
# Sort the dataset by column 'Total_Deaths' to get the top five causes of death for Neoplasm
total_mortality_Italy_neoplasm_sorted=total_mortality_Italy_neoplasm.sort_values('Total_Deaths', a
xis=0, ascending=False, kind='quicksort', na_position='last')
# Select the top five causes of death for Neoplasm
top_5_causes_Italy=total_mortality_Italy_neoplasm_sorted.head(5).copy(deep=True)
# Reset the index
top_5_causes_Italy=top_5_causes_Italy.reset_index(drop=True)

top_5_causes_Italy
```

Out[359]:

	Cause_3digits	Total_Deaths
0	C34	430069
1	C18	182802
2	C50	156002
3	C16	132676
4	C25	132125

In [360]:
```
# Look up the disease each ICD-10 code refers to on  'https://icd.who.int/browse10/2016/en'
# Rename the causes for presentation
top_5_causes_Italy['Cause_3digits']=['Malignant neoplasm of bronchus and lung', 'Malignant neoplas
m of colon', 'Malignant neoplasm of breast', 'Malignant neoplasm of stomach', 'Malignant neoplasm
of pancreas']

top_5_causes_Italy
```

Out[360]:

	Cause_3digits	Total_Deaths
0	Malignant neoplasm of bronchus and lung	430069
1	Malignant neoplasm of colon	182802
2	Malignant neoplasm of breast	156002
3	Malignant neoplasm of stomach	132676
4	Malignant neoplasm of pancreas	132125

Calculate the proportion of overall deaths

In [361]:
```
# Calculate total number of deaths due to Neoplasm
all_causes_Italy=total_mortality_Italy_neoplasm.Total_Deaths.sum()
all_causes_Italy
```

Out[361]: 2248661

In [362]:
```
# Calculate number of death dut to Neoplasm other than the top five causes
other_causes_Italy=all_causes_Italy-top_5_causes_Italy.Total_Deaths.sum()
other_causes_Italy
```

Out[362]: 1214987

In [363]:
```
# Add the 6th row which refers to remainder of causes
top_5_causes_Italy.loc[5]={'Cause_3digits':'Remainder of malignant neoplasms','Total_Deaths':other
_causes_Italy}
top_5_causes_Italy
```

Out[363]:

	Cause_3digits	Total_Deaths
0	Malignant neoplasm of bronchus and lung	430069
1	Malignant neoplasm of colon	182802
2	Malignant neoplasm of breast	156002
3	Malignant neoplasm of stomach	132676
4	Malignant neoplasm of pancreas	132125
5	Remainder of malignant neoplasms	1214987

In [364]:

```
# Calculate the proportion of overall deaths and generate a new column to store the result
top_5_causes_Italy['Proportion']=top_5_causes_Italy['Total_Deaths'] / all_causes_Italy
# Round off the value to the nearest 3 decimal places.
top_5_causes_Italy['Proportion'] = top_5_causes_Italy['Proportion'].apply(lambda x: round(x,3))
top_5_causes_Italy
```

Out[364]:

	Cause_3digits	Total_Deaths	Proportion
0	Malignant neoplasm of bronchus and lung	430069	0.191
1	Malignant neoplasm of colon	182802	0.081
2	Malignant neoplasm of breast	156002	0.069
3	Malignant neoplasm of stomach	132676	0.059
4	Malignant neoplasm of pancreas	132125	0.059
5	Remainder of malignant neoplasms	1214987	0.540

3.1 Generate a table with the cause of death, the number of deaths, and the proportion of overall deaths.

In [365]:

```
# Rename the columns for presentation
top_5_causes_Italy.columns=['Cause_of_deaths', 'Number_of_deaths', 'Proportion_of_overall_deaths']
top_5_causes_Italy
```

Out[365]:

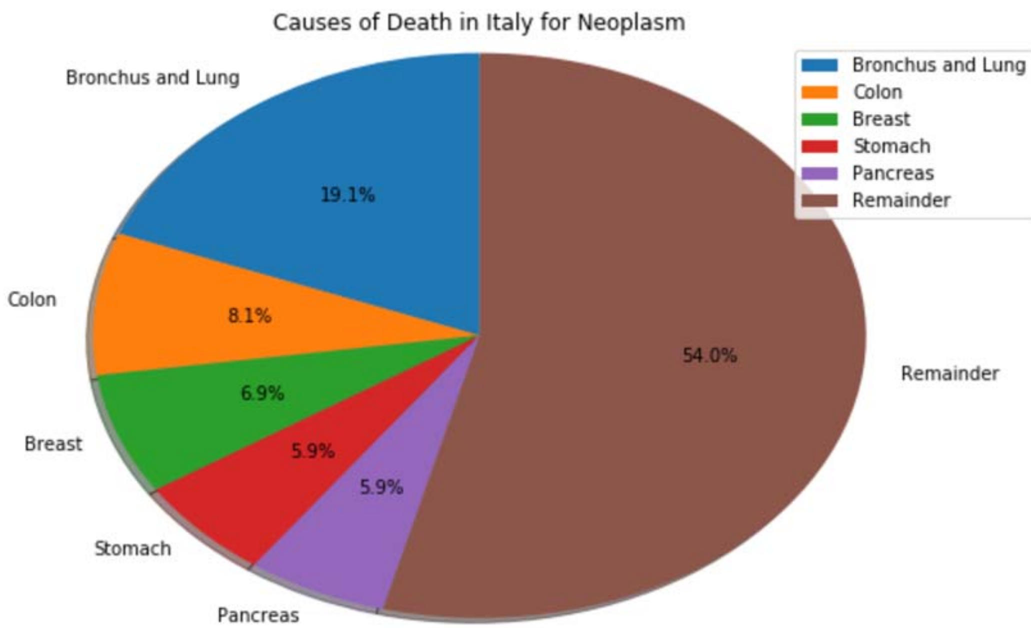
	Cause_of_deaths	Number_of_deaths	Proportion_of_overall_deaths
0	Malignant neoplasm of bronchus and lung	430069	0.191
1	Malignant neoplasm of colon	182802	0.081
2	Malignant neoplasm of breast	156002	0.069
3	Malignant neoplasm of stomach	132676	0.059
4	Malignant neoplasm of pancreas	132125	0.059
5	Remainder of malignant neoplasms	1214987	0.540

- Q3.1 The top five causes of death in Italy across all years for Neoplasms are: Malignant neoplasm of bronchus and lung, colon, breast, stomach and pancreas.

  They make up almost half of deaths for Neoplasm. Malignant neoplasm of bronchus and lung alone accounts for 19% of death, which is relatively high.

3.2 Generate a pie chart to visualize the proportion of deaths

In [366]:
```
# Define labels
cause_of_death_Italy=['Bronchus and Lung', 'Colon', 'Breast', 'Stomach', 'Pancreas', 'Remainder']
# Portion covered by each label
number_of_deaths_Italy=top_5_causes_Italy.Number_of_deaths

# Plot the pie chart
plt.figure(figsize=(8, 6))
plt.pie(number_of_deaths_Italy, labels = cause_of_death_Italy, startangle=90, shadow = True, radiu
s = 1.2, autopct = '%1.1f%%')
# Plot a lenged on the upper right of the pie chart
plt.legend(loc='upper right', bbox_to_anchor=(1.2, 1))
plt.title('Causes of Death in Italy for Neoplasm')

plt.show()
plt.close()
```



- Q3.2 The pie chart visualizes the causes of death in Italy across all years for Neoplasms, with the top 5 causes highlightened. It can easily be observed, as mentioned before, that the top 5 causes are of high prevalence, especially the malignant neoplasm of bronchus.

4. Are there differences by age group for deaths from Neoplasms (C00-D48) in Australia for 2010?

4.1 Identify the top five age groups in Australia dying with a Neoplasms cause of death.

Identify the dataset of age groups in Australia dying with a Neoplasms in 2010

In [367]:
```
# Look up the country code for Australia
country_name='Australia'
country_codes_Australia=country_codes['Country'][country_codes.Name==country_name].values[0]
country_codes_Australia
```

Out[367]: 5020

In [368]:
```
# The subset of mortality data is matched by the country code, year of interest and ICD-10 code
# Select columns 'Deaths2' to 'Deaths26' which contains number of deaths of each age group for eac
h cause and gender
mortality_Australia_2010_neoplasm=mortality[(mortality.Country==country_codes_Australia)&(mortalit
y.Year==2010)&(mortality.Cause.str.match(neoplasm_regex))][['Deaths2', 'Deaths3', 'Deaths4', 'Deat
hs5', 'Deaths6', 'Deaths7', 'Deaths8', 'Deaths9', 'Deaths10', 'Deaths11', 'Deaths12', 'Deaths13',
'Deaths14', 'Deaths15', 'Deaths16', 'Deaths17', 'Deaths18', 'Deaths19', 'Deaths20', 'Deaths21', 'D
eaths22', 'Deaths23', 'Deaths24', 'Deaths25', 'Deaths26']]
mortality_Australia_2010_neoplasm.head()
```

Out[368]:

	Deaths2	Deaths3	Deaths4	Deaths5	Deaths6	Deaths7	Deaths8	Deaths9	Deaths10	Deaths
2144494	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2144495	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2144496	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
2144497	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2144498	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 25 columns

Detect missing values

In [369]:
```
# Detect missing values
mortality_Australia_2010_neoplasm.count()
```

Out[369]:
```
Deaths2     562
Deaths3     562
Deaths4     562
Deaths5     562
Deaths6     562
Deaths7     562
Deaths8     562
Deaths9     562
Deaths10    562
Deaths11    562
Deaths12    562
Deaths13    562
Deaths14    562
Deaths15    562
Deaths16    562
Deaths17    562
Deaths18    562
Deaths19    562
Deaths20    562
Deaths21    562
Deaths22    562
Deaths23    562
Deaths24    562
Deaths25    562
Deaths26    562
dtype: int64
```

There is no missing value in the dataset of interest.

In [370]:
```
# Sum up the values of each column to get total number of deaths of each age group
mortality_Australia_2010_neoplasm_age_group=pd.DataFrame(mortality_Australia_2010_neoplasm.apply(l
ambda x: x.sum()))
mortality_Australia_2010_neoplasm_age_group.head()

# Reset the index
mortality_Australia_2010_neoplasm_age_group.reset_index(inplace=True)
# Rename the columns
mortality_Australia_2010_neoplasm_age_group.columns=['Age_Group','Deaths']

mortality_Australia_2010_neoplasm_age_group.head()
```

Out[370]:

	Age_Group	Deaths
0	Deaths2	11.0
1	Deaths3	7.0
2	Deaths4	11.0
3	Deaths5	7.0
4	Deaths6	8.0

In [371]:
```
# Sort the dataset by column 'Deaths' to get the top five age groups dying with a Neoplasms cause of death
mortality_Australia_2010_neoplasm_age_group_sorted=mortality_Australia_2010_neoplasm_age_group.sort_values('Deaths', axis=0, ascending=False, kind='quicksort', na_position='last')
top_5_age_groups_Australia_2010=mortality_Australia_2010_neoplasm_age_group_sorted.head(5).copy(deep=True)
# Reset the index
top_5_age_groups_Australia_2010=top_5_age_groups_Australia_2010.reset_index(drop=True)

top_5_age_groups_Australia_2010
```

Out[371]:

	Age_Group	Deaths
0	Deaths22	7167.0
1	Deaths21	6291.0
2	Deaths20	5713.0
3	Deaths23	5520.0
4	Deaths19	4768.0

In [372]:
```
# Look up in documentation which age group each row represents
top_5_age_groups_Australia_2010['Age_Group']=['80-84', '75-79', '70-74', '85-89', '65-69']
top_5_age_groups_Australia_2010
```

Out[372]:

	Age_Group	Deaths
0	80-84	7167.0
1	75-79	6291.0
2	70-74	5713.0
3	85-89	5520.0
4	65-69	4768.0

- Q4.1 The top five age groups in Australia dying with a Neoplasms cause of death in 2010 are: age groups 80-84, 75-79, 70-74, 85-89 and 65-69, which indicates that old people in general are in higher risk of deaths due to Neoplasms.

5. Compare and contrast the frequency of deaths by Neoplasms in Italy and Australia in 2010.

5.1 Combine information on the population and deaths to calculate the frequency of deaths by Neoplasms in Italy and Australia in 2010

5.1.1.1 Calculate the population in 2010 for Italy

In [373]:
```
# The population in 2010 for Italy
total_population_Italy_2010
```

Out[373]: 60483386.0

5.1.1.2 Calculate the total number of death caused by Neoplasms in 2010 for Italy

In [374]:
```
# The subset of mortality data is matched by the country code , year of interest and ICD-10 code
mortality_Italy_2010_neoplasm=mortality[(mortality.Country==country_codes_Italy)&(mortality.Year==
2010)&(mortality.Cause.str.match(neoplasm_regex))]
mortality_Italy_2010_neoplasm.head()
```

Out[374]:

	Country	Admin1	SubDiv	Year	List	Cause	Sex	Frmat	IM_Frmat	Deaths1	...	Deaths21	D
1577587	4180	NaN	NaN	2010	104	C000	1	00	01	3	...	0.0	0
1577588	4180	NaN	NaN	2010	104	C000	2	00	01	4	...	0.0	0
1577589	4180	NaN	NaN	2010	104	C001	1	00	01	17	...	3.0	6
1577590	4180	NaN	NaN	2010	104	C001	2	00	01	10	...	2.0	2
1577591	4180	NaN	NaN	2010	104	C006	1	00	01	1	...	0.0	0

5 rows × 39 columns

In [375]:
```
# Use deep copy in case the initial dataset would be changed when generating a new column
# To save memory, only select columns 'Cause' and 'Deaths1', which contain cause of death and numb
er of death at all ages
mortality_Italy_2010_neoplasm_3digits=mortality_Italy_2010_neoplasm[['Cause','Deaths1']].copy(deep
=True)
mortality_Italy_2010_neoplasm_3digits.head()
```

Out[375]:

	Cause	Deaths1
1577587	C000	3
1577588	C000	4
1577589	C001	17
1577590	C001	10
1577591	C006	1

In [376]:
```
# Convert 4-digit codes into 3-digit ones and store the new codes in column 'Cause_3digits'
mortality_Italy_2010_neoplasm_3digits['Cause_3digits']=mortality_Italy_2010_neoplasm_3digits['Caus
e'].apply(lambda x: str(x)[0:3])
mortality_Italy_2010_neoplasm_3digits.head()
# Sum up number of death of each age group grouping by the 3-digit ICD-10 codes, to get total numb
er of deaths due to each base type of disease.
total_mortality_Italy_2010_neoplasm = pd.DataFrame(mortality_Italy_2010_neoplasm_3digits.groupby(m
ortality_Italy_2010_neoplasm_3digits.Cause_3digits).apply(lambda subf: subf['Deaths1'].sum()))
# Rename the column
total_mortality_Italy_2010_neoplasm.columns=['Total_Deaths']
# Reset the index
total_mortality_Italy_2010_neoplasm.reset_index(inplace=True)

total_mortality_Italy_2010_neoplasm.head()
```

Out[376]:

	Cause_3digits	Total_Deaths
0	C00	66
1	C01	95
2	C02	461
3	C03	32
4	C04	43

In [377]:
```
# Sort the dataset by column 'Total_Deaths' to get the top five causes of death for Neoplasm
total_mortality_Italy_2010_neoplasm_sorted=total_mortality_Italy_2010_neoplasm.sort_values('Total_
Deaths', axis=0, ascending=False, kind='quicksort', na_position='last')
top_5_causes_Italy_2010=total_mortality_Italy_2010_neoplasm_sorted.head(5).copy(deep=True)
# Resetthe index
top_5_causes_Italy_2010=top_5_causes_Italy_2010.reset_index(drop=True)

top_5_causes_Italy_2010
```

Out[377]:

	Cause_3digits	Total_Deaths
0	C34	33696
1	C18	14547
2	C50	12238
3	C25	10512
4	C16	10075

In [378]:
```
# Calculate total number of deaths caused by Neoplasm
all_causes_Italy_2010=total_mortality_Italy_2010_neoplasm.Total_Deaths.sum()
other_causes_Italy_2010=all_causes_Italy_2010-top_5_causes_Italy_2010.Total_Deaths.sum()

# The total number of death caused by Neoplasms in 2010 for Italy
all_causes_Italy_2010
```

Out[378]: 175046

5.1.1.3 Calculate the frequency of deaths by Neoplasms in 2010 for Italy

In [379]:
```
# Calculate prevalence of deaths by Neoplasms in 2010 for Italy (per 1,000,000 people)
prevalence_Italy_2010_neoplasm=all_causes_Italy_2010/total_population_Italy_2010 * 1000000
prevalence_Italy_2010_neoplasm
```

Out[379]: 2894.117072083233

5.1.2.1 Calculate the population in 2010 for Australia

In [380]:
```
# The population in 2010 for Italy
population_Australia_2010=population[(population.Country==country_codes_Australia)&(population.Yea
r==2010)]
total_population_Australia_2010=sum(population_Australia_2010.Pop1)
total_population_Australia_2010
```

Out[380]: 22297515.0

5.1.2.2 Calculate the total number of death caused by Neoplasms in 2010 for Australia

In [381]:
```
# The subset of mortality data is matched by the country code , year of interest and ICD-10 code
mortality_Australia_2010_neoplasm=mortality[(mortality.Country==country_codes_Australia)&(mortalit
y.Year==2010)&(mortality.Cause.str.match(neoplasm_regex))]
mortality_Australia_2010_neoplasm.head()
```

Out[381]:

	Country	Admin1	SubDiv	Year	List	Cause	Sex	Frmat	IM_Frmat	Deaths1	...	Deaths21	D
2144494	5020	NaN	NaN	2010	104	C001	1	00	01	2	...	0.0	1
2144495	5020	NaN	NaN	2010	104	C001	2	00	01	2	...	0.0	1
2144496	5020	NaN	NaN	2010	104	C009	1	00	01	2	...	0.0	1
2144497	5020	NaN	NaN	2010	104	C009	2	00	01	5	...	2.0	0
2144498	5020	NaN	NaN	2010	104	C01	1	00	01	20	...	3.0	0

5 rows × 39 columns

In [382]:
```
# Use deep copy in case the initial dataset would be changed when generating a new column
# To save memory, only select columns 'Cause' and 'Deaths1', which contain cause of death and numb
er of death at all ages
mortality_Australia_2010_neoplasm_3digits=mortality_Australia_2010_neoplasm[['Cause','Deaths1']].c
opy(deep=True)
mortality_Australia_2010_neoplasm_3digits.head()
```

Out[382]:

	Cause	Deaths1
2144494	C001	2
2144495	C001	2
2144496	C009	2
2144497	C009	5
2144498	C01	20

In [383]:

```
# Convert 4-digit codes into 3-digit ones and store the new codes in column 'Cause_3digits'
mortality_Australia_2010_neoplasm_3digits['Cause_3digits']=mortality_Australia_2010_neoplasm_3digi
ts['Cause'].apply(lambda x: str(x)[0:3])
mortality_Australia_2010_neoplasm_3digits.head()
# Sum up number of death of each age group grouping by the 3-digit ICD-10 codes, to get total numb
er of deaths due to each base type of disease.
total_mortality_Australia_2010_neoplasm = pd.DataFrame(mortality_Australia_2010_neoplasm_3digits.g
roupby(mortality_Australia_2010_neoplasm_3digits.Cause_3digits).apply(lambda subf: subf['Deaths1']
.sum()))
# Rename the column
total_mortality_Australia_2010_neoplasm.columns=['Total_Deaths']
# Reset the index
total_mortality_Australia_2010_neoplasm.reset_index(inplace=True)

total_mortality_Australia_2010_neoplasm.head()
```

Out[383]:

	Cause_3digits	Total_Deaths
0	C00	11
1	C01	27
2	C02	177
3	C03	14
4	C04	27

In [384]:

```
# Sort the dataset by column 'Total_Deaths' to get the top five causes of death for Neoplasm
total_mortality_Australia_2010_neoplasm_sorted=total_mortality_Australia_2010_neoplasm.sort_values
('Total_Deaths', axis=0, ascending=False, kind='quicksort', na_position='last')
top_5_causes_Australia_2010=total_mortality_Australia_2010_neoplasm_sorted.head(5).copy(deep=True)
# Resetthe index
top_5_causes_Australia_2010=top_5_causes_Australia_2010.reset_index(drop=True)

top_5_causes_Australia_2010
```

Out[384]:

	Cause_3digits	Total_Deaths
0	C34	8098
1	C61	3236
2	C50	2866
3	C80	2783
4	C25	2434

In [385]:

```
# Calculate total number of deaths caused by Neoplasm
all_causes_Australia_2010=total_mortality_Australia_2010_neoplasm.Total_Deaths.sum()
other_causes_Australia_2010=all_causes_Australia_2010-top_5_causes_Australia_2010.Total_Deaths.sum
()

# The total number of death caused by Neoplasms in 2010 for Australia
all_causes_Australia_2010
```

Out[385]: 43316

5.1.1.3 Calculate the frequency of deaths by Neoplasms in 2010 for Italy

In [386]:
```
# Calculate prevalence of deaths by Neoplasms in 2010 for Australia (per 1,000,000 people)
prevalence_Australia_2010_neoplasm=all_causes_Australia_2010/total_population_Australia_2010 * 100
0000
prevalence_Australia_2010_neoplasm
```

Out[386]: 1942.6380024859272

Generate a table to compare the frequency of deaths by Neoplasms in Italy and Australia in 2010

In [387]:
```
# Generate a table to compare the frequency of deaths by Neoplasms in Italy and Australia in 2010
prevalence = pd.DataFrame(
    {'Country':['Italy', 'Australia'],
     'Population':[total_population_Italy_2010, total_population_Australia_2010],
     'Total Number of Deaths':[all_causes_Italy_2010, all_causes_Australia_2010],
     'Prevalence of Death by Neoplams':[prevalence_Italy_2010_neoplasm, prevalence_Australia_2010_
neoplasm]})
prevalence
```

Out[387]:

	Country	Population	Prevalence of Death by Neoplams	Total Number of Deaths
0	Italy	60483386.0	2894.117072	175046
1	Australia	22297515.0	1942.638002	43316

- Q5.1 As shown in the table above, people in Italy have higer prevalence of deaths by Neoplasms in 2010. The prevalence in Italy is 2,894 cases per 1,000,000 people, almost 1.5 times as high as that of Australia.

5.2 Compare the top five causes of death by Neoplasms in Italy and Australia in 2010

5.2.1 Calculate the top five causes of death by Neoplasms in Italy in 2010

In [388]:
```
# Look up the disease each ICD-10 code refers to on  'https://icd.who.int/browse10/2016/en'
# Rename the causes for presentation
top_5_causes_Italy_2010['Cause_3digits']=['Malignant neoplasm of bronchus and lung', 'Malignant neoplasm of colon', 'Malignant neoplasm of breast', 'Malignant neoplasm of pancreas', 'Malignant neoplasm of stomach']

# Add the 6th row which refers to remainder of causes
top_5_causes_Italy_2010.loc[5]={'Cause_3digits':'Remainder of malignant neoplasms','Total_Deaths':other_causes_Italy_2010}
top_5_causes_Italy_2010
```

Out[388]:

	Cause_3digits	Total_Deaths
0	Malignant neoplasm of bronchus and lung	33696
1	Malignant neoplasm of colon	14547
2	Malignant neoplasm of breast	12238
3	Malignant neoplasm of pancreas	10512
4	Malignant neoplasm of stomach	10075
5	Remainder of malignant neoplasms	93978

In [389]:
```
# Calculate the proportion of overall deaths and generate a new column to store the result
# Round off the value to the nearest 3 decimal places.
top_5_causes_Italy_2010['Proportion']=top_5_causes_Italy_2010['Total_Deaths'] / all_causes_Italy_2010
top_5_causes_Italy_2010['Proportion'] = top_5_causes_Italy_2010['Proportion'].apply(lambda x: round(x,3))
top_5_causes_Italy_2010
```

Out[389]:

	Cause_3digits	Total_Deaths	Proportion
0	Malignant neoplasm of bronchus and lung	33696	0.192
1	Malignant neoplasm of colon	14547	0.083
2	Malignant neoplasm of breast	12238	0.070
3	Malignant neoplasm of pancreas	10512	0.060
4	Malignant neoplasm of stomach	10075	0.058
5	Remainder of malignant neoplasms	93978	0.537

In [390]:
```
# Rename the columns for presentation
top_5_causes_Italy_2010.columns=['Cause_of_deaths', 'Number_of_deaths', 'Proportion_of_overall_dea
ths']
top_5_causes_Italy_2010
```

Out[390]:

	Cause_of_deaths	Number_of_deaths	Proportion_of_overall_deaths
0	Malignant neoplasm of bronchus and lung	33696	0.192
1	Malignant neoplasm of colon	14547	0.083
2	Malignant neoplasm of breast	12238	0.070
3	Malignant neoplasm of pancreas	10512	0.060
4	Malignant neoplasm of stomach	10075	0.058
5	Remainder of malignant neoplasms	93978	0.537

5.2.2 Calculate the top five causes of death by Neoplasms in Italy in 2010

In [391]:
```
# Look up the disease each ICD-10 code refers to on  'https://icd.who.int/browse10/2016/en'
# Rename the causes for presentation
top_5_causes_Australia_2010['Cause_3digits']=['Malignant neoplasm of bronchus and lung', 'Malignan
t neoplasm of prostate', 'Malignant neoplasm of breast', 'Malignant neoplasm, without specificatio
n of site', 'Malignant neoplasm of pancreas']

# Add the 6th row which refers to remainder of causes
top_5_causes_Australia_2010.loc[5]={'Cause_3digits':'Remainder of malignant neoplasms','Total_Deat
hs':other_causes_Australia_2010}
top_5_causes_Australia_2010
```

Out[391]:

	Cause_3digits	Total_Deaths
0	Malignant neoplasm of bronchus and lung	8098
1	Malignant neoplasm of prostate	3236
2	Malignant neoplasm of breast	2866
3	Malignant neoplasm, without specification of site	2783
4	Malignant neoplasm of pancreas	2434
5	Remainder of malignant neoplasms	23899

In [392]:

```
# Calculate the proportion of overall deaths and generate a new column to store the result
# Round off the value to the nearest 3 decimal places.
top_5_causes_Australia_2010['Proportion']=top_5_causes_Australia_2010['Total_Deaths'] / all_causes
_Australia_2010
top_5_causes_Australia_2010['Proportion'] = top_5_causes_Australia_2010['Proportion'].apply(lambda
x: round(x,3))
top_5_causes_Australia_2010
```

Out[392]:

	Cause_3digits	Total_Deaths	Proportion
0	Malignant neoplasm of bronchus and lung	8098	0.187
1	Malignant neoplasm of prostate	3236	0.075
2	Malignant neoplasm of breast	2866	0.066
3	Malignant neoplasm, without specification of site	2783	0.064
4	Malignant neoplasm of pancreas	2434	0.056
5	Remainder of malignant neoplasms	23899	0.552

In [393]:

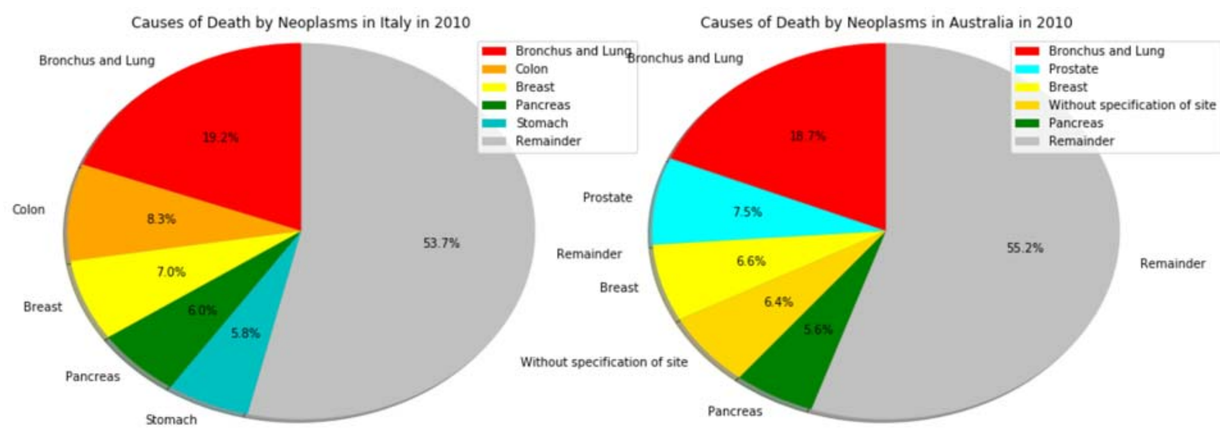
```
# Rename the columns for presentation
top_5_causes_Australia_2010.columns=['Cause_of_deaths', 'Number_of_deaths', 'Proportion_of_overall
_deaths']
top_5_causes_Australia_2010
```

Out[393]:

	Cause_of_deaths	Number_of_deaths	Proportion_of_overall_deaths
0	Malignant neoplasm of bronchus and lung	8098	0.187
1	Malignant neoplasm of prostate	3236	0.075
2	Malignant neoplasm of breast	2866	0.066
3	Malignant neoplasm, without specification of site	2783	0.064
4	Malignant neoplasm of pancreas	2434	0.056
5	Remainder of malignant neoplasms	23899	0.552

Generate a pie chart to visualize the proportion of deaths

In [394]:
```
plt.figure(figsize=(16, 6))

# Define labels
cause_of_death_Italy_2010=['Bronchus and Lung', 'Colon', 'Breast', 'Pancreas', 'Stomach', 'Remaind
er']
cause_of_death_Australia_2010=['Bronchus and Lung', 'Prostate', 'Breast', 'Without specification o
f site', 'Pancreas', 'Remainder']

# Portion covered by each label
number_of_deaths_Italy_2010=top_5_causes_Italy_2010.Number_of_deaths
number_of_deaths_Australia_2010=top_5_causes_Australia_2010.Number_of_deaths

# Set colors to visualise different types of Neoplasm
colors_Italy=['r', 'orange', 'yellow', 'g', 'c', 'silver']
colors_Australia=['r', 'cyan', 'yellow', 'gold', 'g', 'silver']


# Plot the pie charts
fig1=plt.subplot(121)
plt.pie(number_of_deaths_Italy_2010, labels = cause_of_death_Italy_2010, colors=colors_Italy,start
angle=90, shadow = True, radius = 1.2, autopct = '%1.1f%%')
plt.title('Causes of Death by Neoplasms in Italy in 2010')
plt.legend(loc='upper right', bbox_to_anchor=(1.2, 1))

fig1=plt.subplot(122)
plt.pie(number_of_deaths_Australia_2010, labels = cause_of_death_Australia_2010, colors=colors_Aus
tralia, startangle=90, shadow = True, radius = 1.2, autopct = '%1.1f%%')
plt.title('Causes of Death by Neoplasms in Australia in 2010')
plt.legend(loc='upper right', bbox_to_anchor=(1.2, 1))

plt.show()
plt.close()
```



- Q5.2 The bar charts compare the top five causes of death by Neoplasms in Italy and Australia in 2010.
  - Malignant neoplasm of bronchus and lung is the top cause in both countries, accounting for almost 20% of total deaths.
  - Malignant neoplasm of breast and pancreas are among the top 5 causes in both countries and less proportion of people die from these two diseases in Australia than in Italy.
  - Malignant neoplasm of colon and stomach are among top 5 causes in Italy, while malignant neoplasm of prostate and those without specification of site are among top 5 causes in Australia.

5.3 Compare distribution of deaths by age group in Italy and Australia in 2010 for Neoplasms

5.3.1 Distribution of deaths by age group in Italy in 2010 for Neoplasms

In [395]:

```
# The subset of mortality data is matched by the country code , year of interest and ICD-10 code
# Select columns 'Deaths2' to 'Deaths26' which contains number of deaths of each age group for eac
h cause and gender
mortality_Italy_2010_neoplasm = mortality[(mortality.Country==country_codes_Italy)&(mortality.Year
==2010)&(mortality.Cause.str.match(neoplasm_regex))][['Deaths2', 'Deaths3', 'Deaths4', 'Deaths5',
'Deaths6', 'Deaths7', 'Deaths8', 'Deaths9', 'Deaths10', 'Deaths11', 'Deaths12', 'Deaths13', 'Death
s14', 'Deaths15', 'Deaths16', 'Deaths17', 'Deaths18', 'Deaths19', 'Deaths20', 'Deaths21', 'Deaths2
2', 'Deaths23', 'Deaths24', 'Deaths25', 'Deaths26']]
mortality_Italy_2010_neoplasm.head()
```

Out[395]:

	Deaths2	Deaths3	Deaths4	Deaths5	Deaths6	Deaths7	Deaths8	Deaths9	Deaths10	Death
1577587	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1577588	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1577589	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1577590	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1577591	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 25 columns

In [396]:

```
# Sum up the values of each column to get total number of deaths of each age group
mortality_Italy_2010_neoplasm_age_group=pd.DataFrame(mortality_Italy_2010_neoplasm.apply(lambda x:
x.sum())).copy(deep=True)
mortality_Italy_2010_neoplasm_age_group.head()

# Reset the index
mortality_Italy_2010_neoplasm_age_group.reset_index(inplace=True)
# Rename the columns
mortality_Italy_2010_neoplasm_age_group.columns=['Age_Group','Deaths']

mortality_Italy_2010_neoplasm_age_group.head()
```

Out[396]:

	Age_Group	Deaths
0	Deaths2	19.0
1	Deaths3	21.0
2	Deaths4	16.0
3	Deaths5	26.0
4	Deaths6	20.0

In [397]:
```
# Calculate prevalence of deaths by age group in Italy in 2010 by Neoplasms(per 1,000,000 people)
mortality_Italy_2010_neoplasm_age_group['Prevalence']=mortality_Italy_2010_neoplasm_age_group['Deaths']/total_population_Italy_2010 * 1000000
mortality_Italy_2010_neoplasm_age_group['Prevalence'] = mortality_Italy_2010_neoplasm_age_group['Prevalence'].apply(lambda x: round(x,3))
# Look up in documentation which age group each row represents
mortality_Italy_2010_neoplasm_age_group['Age_Group']=['0', '1', '2', '3', '4', '5-9', '10-14', '15-19', '20-24', '25-29', '30-34', '35-39', '40-44', '45-49', '50-54', '55-59', '60-64', '65-69', '70-74', '75-79', '80-84', '85-89', '90-94', '95+', 'unspecified']
mortality_Italy_2010_neoplasm_age_group.head()
```

Out[397]:

	Age_Group	Deaths	Prevalence
0	0	19.0	0.314
1	1	21.0	0.347
2	2	16.0	0.265
3	3	26.0	0.430
4	4	20.0	0.331

5.3.2 Distribution of deaths by age group in Australia in 2010 for Neoplasms

In [398]:
```
# The subset of mortality data is matched by the country code , year of interest and ICD-10 code
# Select columns 'Deaths2' to 'Deaths26' which contains number of deaths of each age group for each cause and gender
mortality_Australia_2010_neoplasm = mortality[(mortality.Country==country_codes_Australia)&(mortality.Year==2010)&(mortality.Cause.str.match(neoplasm_regex))][['Deaths2', 'Deaths3', 'Deaths4', 'Deaths5', 'Deaths6', 'Deaths7', 'Deaths8', 'Deaths9', 'Deaths10', 'Deaths11', 'Deaths12', 'Deaths13', 'Deaths14', 'Deaths15', 'Deaths16', 'Deaths17', 'Deaths18', 'Deaths19', 'Deaths20', 'Deaths21', 'Deaths22', 'Deaths23', 'Deaths24', 'Deaths25', 'Deaths26']]
mortality_Italy_2010_neoplasm.head()
```

Out[398]:

	Deaths2	Deaths3	Deaths4	Deaths5	Deaths6	Deaths7	Deaths8	Deaths9	Deaths10	Death
1577587	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1577588	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1577589	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1577590	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1577591	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5 rows × 25 columns

In [399]:

```
# Sum up the values of each column to get total number of deaths of each age group
mortality_Australia_2010_neoplasm_age_group=pd.DataFrame(mortality_Australia_2010_neoplasm.apply(l
ambda x: x.sum())).copy(deep=True)
mortality_Australia_2010_neoplasm_age_group.head()

# Reset the index
mortality_Australia_2010_neoplasm_age_group.reset_index(inplace=True)
# Rename the columns
mortality_Australia_2010_neoplasm_age_group.columns=['Age_Group','Deaths']

mortality_Australia_2010_neoplasm_age_group.head()
```

Out[399]:

	Age_Group	Deaths
0	Deaths2	11.0
1	Deaths3	7.0
2	Deaths4	11.0
3	Deaths5	7.0
4	Deaths6	8.0

In [400]:

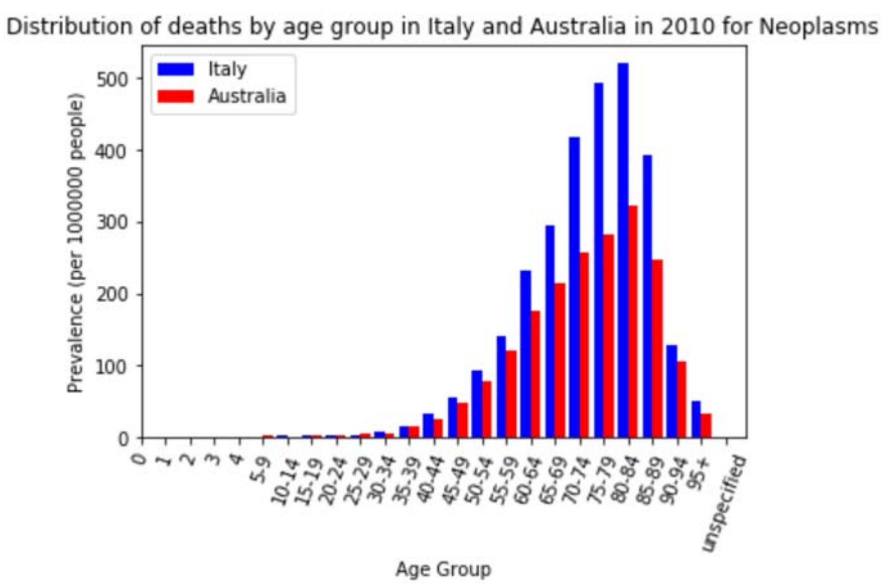
```
# Calculate prevalence of deaths by age group in Italy in 2010 by Neoplasms(per 1,000,000 people)
mortality_Australia_2010_neoplasm_age_group['Prevalence']=mortality_Australia_2010_neoplasm_age_gr
oup['Deaths']/total_population_Australia_2010 * 1000000
mortality_Australia_2010_neoplasm_age_group['Prevalence'] = mortality_Australia_2010_neoplasm_age_
group['Prevalence'].apply(lambda x: round(x,3))
# Look up in documentation which age group each row represents
mortality_Australia_2010_neoplasm_age_group['Age_Group']=['0', '1', '2', '3', '4', '5-9', '10-14',
'15-19', '20-24', '25-29', '30-34', '35-39', '40-44', '45-49', '50-54', '55-59', '60-64', '65-69',
'70-74', '75-79', '80-84', '85-89', '90-94', '95+', 'unspecified']
```

Generate a barchart to compare distribution of deaths by age group in Italy and Australia in 2010 for Neoplasms

In [403]:

```
plt.figure(figsize=(12,9))
ax = plt.subplots()

# Define labels and height of each bar
index = np.arange(25)
prevalence_Italy = mortality_Italy_2010_neoplasm_age_group.Prevalence
prevalence_Australia = mortality_Australia_2010_neoplasm_age_group.Prevalence

# Set width of bars
bar_width=0.4
# Plot the bar chart
ax1=plt.bar(index,prevalence_Italy,bar_width,color='b',label='Italy')
ax2=plt.bar(index+bar_width,prevalence_Australia,bar_width,color='r',label='Australia')

plt.xlabel('Age Group')
plt.ylabel('Prevalence (per 1000000 people)')
plt.title('Distribution of deaths by age group in Italy and Australia in 2010 for Neoplasms')
plt.xlim(1,25)
# Set tick labels
plt.xticks(index+bar_width, ())
plt.xticks(index + bar_width/2, ('0', '1', '2', '3', '4', '5-9', '10-14', '15-19', '20-24', '25-29', '30-34', '35-39', '40-44', '45-49', '50-54', '55-59', '60-64', '65-69', '70-74', '75-79', '80-84', '85-89', '90-94', '95+', 'unspecified'),rotation='70')
plt.legend()

plt.show()
```

<Figure size 864x648 with 0 Axes>



- Q5.3 The histogram visualises the distribution of deaths by age group in Italy and Australia in 2010 for Neoplasms.
  - It can be observed that each age group in Italy in general have higher prevalence of deaths for Neoplams in 2010 the age group in Australia
  - The trend of prevalence against age are similar in two countries. Total prevalence of death for each age group increases rapidly with increase in age, and reaches the peak in age group 80-84.
  - Refering to interpretation of Question 2, the decrease of prevalence of death in older age groups is not due to decrease of populaiton of that age group because the trend still exist using prevalence instead of number of death