DMHR_CCHZ3

January 22, 2019

1 This project is on the Github https://github.com/Hana731/DMHR

2 Assignment A

Background and Aim

National Health Service (NHS)is health services including NHS England, Scotland, Wales and Northern Ireland. Each service provides a comprehensive range of health services, free at the point of use for people ordinarily resident in the United Kingdom (not including dental treatment and optical care). NHS publish Practice level prescribing data each month. The dataset contains list of all medicines, dressing and appliances which are prescribed by the practises in England and dispensed in the community. The NHS has been challenged to make 'efficiency savings', and we have been assigned to review the document and assess prescribing costs.

Datasets: 1. NHS Digital GP Practice Prescribing 2. NHS Digital GP Practice Demographics

(Each monthly data set is very large (over 10 million rows), it may occur unexpected problems by open it directly)

Variables explanation:

SHA/AT: this is code of the Strategic Health Authority (SHA) in which the practice resides (August 2010 to March 2013). From April 2013 this field relates to the Area Team.

PCT/CCG: this relates to the Clinical Commissioning Group (CCG)

Practice Code and names: This is code for the practice. It can potentially be used to linked to other data that uses the practice code as is defined by the NHS Digital Organisation Data Service (ODS). The format is Axxxxx where "A" is a letter and "xxxxx" is a 5-digit number.

BNF code: The BNF code for the drug.

BNF name: The drug is shown by individual preparation name, which may be proprietary or generic, followed by form and strength.

Items: This gives the number of items for this presentation that were dispensed in the specified month. A prescription item refers to a single supply of a medicine, dressing or appliance prescribed on a prescription form. If a prescription form includes three medicines, it is counted as three prescription items.

Net ingredient cost (NIC): This is the basic cost of a drug as used in primary care. This is the cost at list price excluding VAT, i.e. the price listed in the national Drug Tariff or in standard price lists and is not necessarily the price the NHS paid. It does not take into account of any contract prices or discounts, dispensing costs, fees or prescription charge income, so the amount the NHS paid will be different.

Actual Cost: From July 2012 onwards, the formula used to calculate 'Actual Cost' has been changed to include the new reimbursement payments which will be charged back to practices from dispensed prescriptions.

Quantity: The quantity of a drug dispensed is measured in units depending on the formulation of the product, which is given in the drug name.

Processing date: The date is given as the year and month to which the file refers.

Chemical name: This is the International Non-proprietary Name (INN) and is the standard registered name for the active constituent of that medicine, for example omeprazole.

```
In [1]: # import necessary libraries

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

3 Q1. Identify all GP practices located in London. For those practices, describe:

o the total number of patients registered

o the total number of prescriptions

o the total actual cost of these prescriptions (using the ACT COST column)

o the top 10 most frequent drugs prescribed

o the bottom 10 less frequent drugs prescribed

We can see from the first Question is about all the GP practices located in London that is the premise.From the datasets, we need to extra all GPs in London first. We use NHS Digital GP Practice Demographics dataset to extract the GPs in London and combine with NHS Digital GP Practice Prescribing dataset via common key(practise code) to answer further questions.

```
In [2]: #Read NHS Digital GP Practice Prescribing dataset and add new columns name to the data

        cols = ['sha', 'pct', 'practice', 'bnf_code', 'bnf_name', 'items', 'nic', 'act_cost', 
        PDPI = pd.read_csv('/Users/charles/Desktop/T201804PDPI+BNFT.CSV', header=None, names=co
        PDPI.head()
```

```
Out[2]:    sha  pct practice         bnf_code  \
        0  Q44  RTV   Y04937  0401010Z0AAAAAA
        1  Q44  RTV   Y04937  0401020K0AAAHAH
        2  Q44  RTV   Y04937  0401020K0AAAIAI
        3  Q44  RTV   Y04937  0402010ABAAABAB
        4  Q44  RTV   Y04937  0402010ADAAAAAA

                                         bnf_name  items   nic  act_cost  quantity  \
        0  Zopiclone_Tab 7.5mg                          6  1.56      2.12        63
        1  Diazepam_Tab 2mg                             4  0.87      1.15        73
        2  Diazepam_Tab 5mg                             2  0.46      0.56        35
        3  Quetiapine_Tab 25mg                          1  2.60      2.52        14
        4  Aripiprazole_Tab 10mg                        1  1.53      1.53        14
```

```
   period
0  201804
1  201804
2  201804
3  201804
4  201804
```

In [3]:
```
#Read NHS Digital GP Practice Demographics dataset and add new columns name to the dat

cols2 = ['201804', 'practice', 'center_name01', 'center_name02', 'addr01', 'addr02', 'a
ADDR = pd.read_csv('/Users/charles/Desktop/T201804ADDR+BNFT.CSV', header=None, names=co
ADDR.head()
```

Out[3]:
```
   201804 practice                              center_name01  \
0  201804   A81001  THE DENSHAM SURGERY
1  201804   A81002  QUEENS PARK MEDICAL CENTRE
2  201804   A81004  BLUEBELL MEDICAL CENTRE
3  201804   A81005  SPRINGWOOD SURGERY
4  201804   A81006  TENNANT STREET MEDICAL PRACTICE

               center_name02                      addr01  \
0  THE HEALTH CENTRE           LAWSON STREET
1  QUEENS PARK MEDICAL CTR     FARRER STREET
2  TRIMDON AVENUE              ACKLAM
3  SPRINGWOOD SURGERY          RECTORY LANE
4  TENNANT ST MEDICAL PRACT    TENNANT STREET

                      addr02                      addr03 post_code
0  STOCKTON-ON-TEES            CLEVELAND                   TS18 1HU
1  STOCKTON ON TEES            CLEVELAND                   TS18 2AW
2  MIDDLESBROUGH                                           TS5 8SB
3  GUISBOROUGH                                             TS14 7DJ
4  STOCKTON-ON-TEES            CLEVELAND                   TS18 2AT
```

In [4]:
```
# From the ADDR dataset, we can extra the GPs in London by either address or post_code
# We check the address(addr01:street addr02:city addr03:Province) to identify the GPs

practice_London_addr = ADDR.practice[(ADDR.addr02.str.strip() == 'LONDON')|(ADDR.addr0
practice_London_addr.values
practice_London_addr.count()

# London GPs ( slicing London GPs via the practise code from GP_demograph)

GP_demograph = pd.read_csv('/Users/charles/Desktop/gp-reg-pat-prac-all.csv')
GP_common_code = list(practice_London_addr.values)
GP_demograph_london = GP_demograph.loc[GP_demograph['CODE'].isin (GP_common_code)]
GP_demograph_london.head()
```

Out[4]:
```
          PUBLICATION EXTRACT_DATE TYPE CCG_CODE ONS_CCG_CODE    CODE  \
3664  GP_PRAC_PAT_LIST    01APR2018   GP      07L    E38000004  Y04786
```

```
3665  GP_PRAC_PAT_LIST    01APR2018   GP      07M    E38000005  E83003
3666  GP_PRAC_PAT_LIST    01APR2018   GP      07M    E38000005  E83005
3667  GP_PRAC_PAT_LIST    01APR2018   GP      07M    E38000005  E83006
3668  GP_PRAC_PAT_LIST    01APR2018   GP      07M    E38000005  E83007

      POSTCODE  SEX  AGE  NUMBER_OF_PATIENTS
3664  IG3 8YB  ALL  ALL                 443
3665  N20 0DH  ALL  ALL                8911
3666   N3 2JP  ALL  ALL                6224
3667  NW2 1HS  ALL  ALL                6885
3668   N3 2AU  ALL  ALL                5706
```

In [5]:
```
#Register patients number

GP_number = GP_demograph_london.NUMBER_OF_PATIENTS.sum()
GP_number
```

Out[5]: 5841956

The total number of registered patients in London is 5841956.

In [6]:
```
#The total number of prescriptions

Prescriptions_london = PDPI.loc[PDPI['practice'].isin (GP_common_code)]
Prescriptions_london.quantity.sum()
```

Out[6]: 510136987

The total number of prescriptions is 510136987.

In [7]:
```
#The total actual cost of these prescriptions (using the ACT COST column)

Prescriptions_COST_london = PDPI.loc[PDPI['practice'].isin (GP_common_code)]
Prescriptions_COST_london.act_cost.sum()
```

Out[7]: 43322000.54

The total actual cost of these prescription is 43322000.54.

In [82]:
```
Prescriptions_sum_London=Prescriptions_london.groupby(['bnf_code']).sum()
# the top 10 most frequent drugs prescribed

Top_drug_sorted = Prescriptions_sum_London.sort_values('quantity',axis=0, ascending=Fa
Top_drug_top10_London = Top_drug_sorted.head(10)
Top_drug_top10_London
#list(Top_drug_top10_London.index)
```

Out[82]:

	items	nic	act_cost	quantity	period
bnf_code					
090402000BBRRA0	4477	96281.92	91808.65	17023232	93838860

```
0601022B0AAABAB  121063  376329.40  353102.30  11706703  158819748
090402000BBAJA0    3655   58826.88   55067.39  10217184   62155632
0106040G0AAAAAA   17330   43081.00   40654.65   9283922  157205316
0407010H0AAAMAM   74463   75152.42   72891.70   7690436  158819748
130201000BBICBW   11641   81147.40   75401.83   6717500  155389080
090402000BBVTA0    1247   71311.05   66923.85   6565947   74062068
090402000BBRMA0     830   69577.20   65085.19   6556352   34912092
090402000BBSIA0    1166   63283.80   59344.98   5455500   55092492
0103050P0AAAAAA  123310  100130.28   98762.26   4665483  163663044
```

In [115]:
```python
#find the drugs according to bnf_code
Prescriptions_london[Prescriptions_london.bnf_code=='090402000BBRRA0'].bnf_name[:1]
```

Out[115]:
```
6051072    Ensure Plus_Milkshake Style Liq (9 Flav)
Name: bnf_name, dtype: object
```

The top 10 most frequent drugs prescribed are:
['090402000BBRRA0 Ensure Plus_Milkshake Style Liq (9 Flav)',
'0601022B0AAABAB Metformin HCl_Tab 500mg',
'090402000BBAJA0 Fortisip Bottle_Liq (8 Flav)',
'0106040G0AAAAAA Lactulose_Soln 3.1g-3.7g/5ml',
'0407010H0AAAMAM Paracet_Tab 500mg',
'130201000BBICBW Dermol 500_Lot',
'090402000BBVTA0 Ensure Compact_Liq (4 Flav)',
'090402000BBRMA0 Fresubin 2kcal_Drink (6 Flav)',
'090402000BBSIA0 Fortisip Compact_Liq (8 Flav)',
'0103050P0AAAAAA Omeprazole_Cap E/C 20mg']

From the top10 prescriptions of london, we need a deeper look at top three and further analyse it. The most frequent prescription is Ensure Plus_Milkshake Style which is a ready-to-drink, milkshake style oral nutritional supplement for people with, or at risk of developing, disease-related malnutrition. The second most frequent prescription is Metformin HCl_Tab 500mg. It is a medcine to treat high blood sugar levels caused by type 2 diabetes. From this we can infer that there a lot of patients in London with type 2 diabetes. Type 2 Diabtet is caused by eating habits, pressure, living styles, obisity and so on. As the data shown, people living in London do not having a healthy life style and under high pressure in general. The third one is Fortisip Bottle_Liq,which is a food for special medical purposes for use undermedical supervison.Fortisip is a nutritionally complete,for the management of disease related malnutrition.

In [94]:
```python
# the bottom 10 drugs prescribed

Top_drug_sorted = Prescriptions_sum_London.sort_values('quantity',axis=0, ascending=T
Top_drug_bottom10_London = Top_drug_sorted[:10]
Top_drug_bottom10_London.index
```

Out[94]:
```
                 items    nic  act_cost  quantity  period
bnf_code
0801030P0AAFIFI      1  13.37     12.41         0  201804
20100000737          1   1.40      1.31         1  201804
20031300053          1  51.97     48.21         1  201804
```

```
20031400045          1   17.70     16.43          1  201804
0402020ABBCABAG      1  734.70    681.37          1  201804
20031400062          1   59.43     55.13          1  201804
21011200274          1   21.28     19.75          1  201804
21270002383          1   40.19     37.28          1  201804
21270002421          1  162.24    150.46          1  201804
21270002468          1    3.18      2.95          1  201804
```

In [96]:
```
#find the drugs according to bnf_code
#Prescriptions_london[Prescriptions_london.bnf_code=='1202010M0AAADAD'].bnf_name
```

The bottom 10 less frequent drugs prescribed are:
'Methotrexate_Inj 7.5mg/0.3ml Pfs',
'Trevicta_Inj 263mg/1.315ml Pfs P/R ',
'Modecate Conc_Inj 100mg/ml 0.5ml Amp' ....

Unlike top 10 prescriptions, there are a lot of prescriptions with one quantity and many of them can not be recognized from the bnf code. We extract three of them to anaylsis. Methotrexate_Inj is indicated for the treatment of active rheumatoid arthritis in adult patients.Trevicta is an antipsychotic medicine for maintenance treatment of schizophrenia in adults. Modecate is also for the treatment and maintenance of schizophrenic patients and those with paranoid psychoses. From the data above, we assume that active rheumatoid arthritis and schizophrenia are not frequenct among London patients.

4 Q2. Identify all GP practices located in Cambridge. For those practices, describe:

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

We repeat the steps what we have done in Q1, except we select Cambridge instead of London.

In [10]:
```
#Extract Cambridge GP's Code and slice Cambridge GP from demograph dataset

practice_Cambridge_addr = ADDR.practice[(ADDR.addr02.str.strip() == 'CAMBRIDGE')|(ADDI
practice_Cambridge_addr.values
practice_Cambridge_addr.count()

#GP_common_code cambridge
GP_common_code2 = list(practice_Cambridge_addr.values)
#Cambridge GP
GP_demograph_Cambridge = GP_demograph.loc[GP_demograph['CODE'].isin (GP_common_code2)]
GP_demograph_Cambridge.head()
```

Out[10]:
```
          PUBLICATION EXTRACT_DATE TYPE CCG_CODE ONS_CCG_CODE    CODE  \
3050  GP_PRAC_PAT_LIST    01APR2018   GP      06H    E38000026  D81001
3051  GP_PRAC_PAT_LIST    01APR2018   GP      06H    E38000026  D81002
3052  GP_PRAC_PAT_LIST    01APR2018   GP      06H    E38000026  D81003
3054  GP_PRAC_PAT_LIST    01APR2018   GP      06H    E38000026  D81005
```

```
3057  GP_PRAC_PAT_LIST    01APR2018   GP      06H    E38000026  D81009

        POSTCODE  SEX  AGE  NUMBER_OF_PATIENTS
3050   CB2 1EH   ALL  ALL               12057
3051   CB3 0DB   ALL  ALL               16939
3052   CB1 2PY   ALL  ALL                9927
3054   CB3 9HS   ALL  ALL               14941
3057  CB22 5FY   ALL  ALL                9071
```

In [11]:
```
#Register patients number

GP_number2 = GP_demograph_Cambridge.NUMBER_OF_PATIENTS.sum()
GP_number2
```

Out[11]: 311579

The total number of registered patients in Cambridge is 311579.

In [12]:
```
#the total number of prescriptions

Prescriptions_Cambridge = PDPI.loc[PDPI['practice'].isin (GP_common_code2)]
Prescriptions_Cambridge.quantity.sum()
```

Out[12]: 25232152

The total number of prescriptions of Cambridge is 25232152.

In [13]:
```
#the total actual cost of these prescriptions (using the ACT COST column)

Prescriptions_COST_Cambridge = PDPI.loc[PDPI['practice'].isin (GP_common_code2)]
Prescriptions_COST_Cambridge.act_cost.sum()
```

Out[13]: 2434403.94

The total actual cost of these prescriptions of Cambridge is 2434403.94.

In [14]:
```
Prescriptions_Cambridge.quantity.sum()
```

Out[14]: 25232152

In [111]:
```
Prescriptions_sum_Cambridge=Prescriptions_Cambridge.groupby(['bnf_code']).sum()
# the top 10 most frequent drugs prescribed

Top_drug_sorted2 = Prescriptions_sum_Cambridge.sort_values('quantity',axis=0, ascendi
Top_drug_top10 = Top_drug_sorted2.head(10)
Top_drug_top10
#list(Top_drug_top10.index)
```

Out[111]:

bnf_code	items	nic	act_cost	quantity	period
090402000BBSIA0	302	10725.65	10019.74	924625	5650512
090402000BBGYA0	27	9370.26	8690.25	651324	2421648
0407010H0AAAMAM	4565	6334.40	6012.26	573923	6457728
090402000BBAJA0	152	2859.36	2722.00	508936	4439688
130201000BBICBW	775	5405.80	5021.06	447500	6659532
0103050P0AAAAAA	11688	9533.34	9128.05	443650	6457728
090402000BBLMA0	23	7372.09	6837.07	437716	2623452
0106040G0AAAAAA	704	1953.93	1847.82	420220	6054120
0601022B0AAABAB	3620	10553.50	9866.12	328345	6255924
090402000BBGXA0	15	5790.90	5370.58	298500	1816236

In [114]:
```
#find the drugs according to bnf_code
#Prescriptions_Cambridge[Prescriptions_Cambridge.bnf_code=='0407010H0AAAMAM'].bnf_na
```

Out[114]:
```
4184402    Paracet_Tab 500mg
Name: bnf_name, dtype: object
```

the top 10 most frequent drugs prescribed:
['090402000BBSIA0 Fortisip Compact_Liq (8 Flav)',
'090402000BBGYA0 Nutrison Pack_Energy ',
'0407010H0AAAMAM Paracet_Tab 500mg',
'090402000BBAJA0 Fortisip Bottle_Liq (8 Flav) ',
'130201000BBICBW Dermol 500_Lot',
'0103050P0AAAAAA Omeprazole_Cap E/C 20mg',
'090402000BBLMA0 Nutrison Pack_Energy M/Fibre',
'0106040G0AAAAAA Lactulose_Soln 3.1g-3.7g/5ml',
'0601022B0AAABAB Metformin HCl_Tab 500mg',
'090402000BBGXA0 Nutrison Pack_Conc Liq ']

Same as London top10 prescriptions, we analyse top three. Fortisip Bottle_Liq and Nutrison pack_energy are foods for special medical purposes for use undermedical supervison. Paracet_Tab is used to treat mild to moderate pain (from headaches, menstrual periods, toothaches, backaches, osteoarthritis, or cold/flu aches and pains) and to reduce fever. The patients in Cambridge are likely to need extra nutruion supplyment from the data above.

In [118]:
```
# the bottom 10 less frequent drugs prescribed

Bottom_drug_sorted2 = Prescriptions_sum_Cambridge.sort_values('quantity',axis=0, asc
Bottom_drug_top10 = Bottom_drug_sorted2
Bottom_drug_top10
```

Out[118]:

bnf_code	items	nic	act_cost	quantity	period
1308010Z0BBABAB	1	65.00	60.28	0	201804
21010230125	1	4.18	3.89	1	201804
23301083062	1	50.37	46.71	1	201804
21210000022	1	4.95	4.60	1	201804
23301083061	1	50.37	46.71	1	201804

23301083059	1	50.37	46.73	1	201804
23301023195	1	25.50	23.65	1	201804
23301023186	1	12.24	11.35	1	201804
23301023127	1	12.24	11.35	1	201804
23301023105	1	25.50	23.65	1	201804
23301003007	1	6.97	6.46	1	201804
23300263353	1	47.32	43.88	1	201804
23300263348	1	47.32	43.88	1	201804
23300263246	1	63.66	59.04	1	201804
23300263072	1	66.41	61.59	1	201804
20090000494	1	0.77	0.71	1	201804
20090000506	1	1.76	1.64	1	201804
23250262508	1	9.89	9.17	1	201804
1404000AMBBAAAA	1	105.00	97.38	1	201804
21220000130	1	8.87	8.23	1	201804
20100000310	1	1.77	1.65	1	201804
21220000232	1	4.00	3.71	1	201804
23150101504	1	14.78	13.72	1	201804
20100000320	1	3.37	3.14	1	201804
0402020ABBBAAAA	1	183.92	170.58	1	201804
22902409045	1	91.24	84.62	1	201804
22902409041	1	28.01	25.98	1	201804
22902409010	1	75.53	70.05	1	201804
22900759004	1	14.55	13.49	1	201804
1307000Q0AAAAAA	1	3.00	2.79	1	201804
...	...	...	...	...	...
090402000BBPGA0	5	1429.84	1326.10	122000	807216
0602010V0AABXBX	3706	4408.45	4177.63	127214	6457728
090401000BBTHA0	51	3598.41	3358.62	128400	3834276
0602010V0AABWBW	3795	8981.98	8424.95	134382	6457728
0602010V0AABZBZ	3897	4705.17	4443.61	137118	6457728
090401000BBMBA0	10	1204.08	1116.77	138400	1210824
21220000214	298	1571.90	1460.91	146000	5045100
0408010G0AAABAB	1335	12171.16	11390.83	147392	6457728
130201000BBJGCA	301	1902.79	1767.81	158300	5852316
090402000BBHCA0	9	2229.36	2067.61	159108	1210824
0101021B0BIABAH	259	630.06	587.02	161550	6255924
0209000A0AAABAB	5737	2005.31	2009.05	170141	6457728
0206020A0AAAAAA	5463	9062.78	8515.08	176667	6457728
0403010B0AAAGAG	3855	6833.41	6423.29	197091	6659532
0212000B0AAABAB	6416	5448.75	5181.29	208712	6255924
090402000BBNGA0	9	2828.04	2622.79	228000	1210824
130201000BBAFA4	459	3041.52	2824.81	235500	6054120
090402000BBUBA0	57	4048.00	3755.60	253000	4237884
21220000242	533	1353.57	1261.79	271800	5650512
090401000BBGFA0	53	2876.48	2701.83	284800	3228864
090402000BBGXA0	15	5790.90	5370.58	298500	1816236
0601022B0AAABAB	3620	10553.50	9866.12	328345	6255924

```
0106040G0AAAAAA    704   1953.93   1847.82    420220  6054120
090402000BBLMA0     23   7372.09   6837.07    437716  2623452
0103050P0AAAAAA  11688   9533.34   9128.05    443650  6457728
130201000BBICBW    775   5405.80   5021.06    447500  6659532
090402000BBAJA0    152   2859.36   2722.00    508936  4439688
0407010H0AAAMAM   4565   6334.40   6012.26    573923  6457728
090402000BBGYA0     27   9370.26   8690.25    651324  2421648
090402000BBSIA0    302  10725.65  10019.74    924625  5650512

[5694 rows x 5 columns]
```

In [122]:
```
#find the drugs according to bnf_code
#Prescriptions_Cambridge[Prescriptions_Cambridge.bnf_code=='1307000Q0AAAAAA'].bnf_na
```

Out[122]:
```
4187908    Silver Nit Caustic_Pencil 95% BP 1980
Name: bnf_name, dtype: object
```

The bottom 10 less frequent drugs prescribed:
'1308010Z0BBABAB Picato_Gel 500mcg/g ',
'1404000AMBBAAAA Gardasil 9_Vac 0.5ml Pfs ',
'0402020ABBBAAAA Xeplion_Inj 50mg/0.5ml Pfs',
'1307000Q0AAAAAA Silver Nit Caustic_Pencil 95% BP 1980', ...

Same as the Bottom 10 in London, there are many prescriptions have same quantity (1), we just extra four of these as a sample. Picato_Gel 500mcg/g, Gardasil 9_Vac 0.5ml Pfs,Xeplion_Inj 50mg/0.5ml Pfs and Silver Nit Caustic_Pencil 95% BP 1980 are four of bottom 10.

5 3. Describe total number of prescriptions and their total actual cost (using the ACT COST column) across all practices for drugs related to:

o cardiovascular disease (British National Formulary chapter 2) o antidepressants (British National Formulary chapter 4.3)

Cardiovascular disease (CVD) is a general term for conditions affecting the heart or blood vessels. And it is one of the main causes of deathh and disability in the UK, but it can be prevented by leading a healthy lifestyle. In our task, we Need to find the total number of prescriptions and total actual cost.

In [18]:
```
#Cardiovascular disease
#In British National Formulary chapter 2, bnf_code is described as 02XXXXXXX
#We use regular expression to extra all the data related to CVD

cardi =PDPI[PDPI.bnf_code.str.contains('^02',regex=True)]
cardi.head()
```

Out[18]:
```
     sha  pct practice         bnf_code  \
28   Q44  RTV   Y05294  0204000R0AAAHAH
29   Q44  RTV   Y05294  0204000R0AAAJAJ
```

```
337  Q44  RXA   Y00327  0202020D0AAAEAE
338  Q44  RXA   Y00327  0202020L0AABBBB
339  Q44  RXA   Y00327  0202020L0AABDBD

                                          bnf_name  items   nic  act_cost  \
28   Propranolol HCl_Tab 10mg                          4  7.12      6.65
29   Propranolol HCl_Tab 40mg                          3  1.35      1.59
337  Bumetanide_Tab 1mg                                1  0.26      0.35
338  Furosemide_Tab 20mg                               1  0.13      0.23
339  Furosemide_Tab 40mg                               1  0.17      0.27

     quantity  period
28        224  201804
29         42  201804
337         6  201804
338        10  201804
339        14  201804
```

In [19]:
```
#total number of prescription CVD
cardi.quantity.sum()
```

Out[19]: 933262147

The total number of presecribtion CVD is 933262147.

In [20]:
```
#total actual cost CVD
cardi.act_cost.sum()
```

Out[20]: 90193834.01999994

The total actual cost of CVD is 90193834.01999994 Depression is a common mental health problem that causes people to experience low mood,loss pleasure and hopeless.It has been considered as one of the most common disease and continuesly increasing mortality under high-pressure daliy life.

Antidepressants are a type of medicine used to treat clinical depression. We can analyse the explicit and implicit information from the prescribtion of Antidepressants.

In [21]:
```
#Antidepressants
#In British National Formulary chapter 4.3, Antidepressants are described as 0403XXXX
#We use regular expression to extra all the data related to Antidepressants

antide =PDPI[PDPI.bnf_code.str.contains('^0403',regex=True)]
antide.head()
```

Out[21]:
```
    sha  pct practice         bnf_code  \
9   Q44  RTV   Y04937  0403010X0AAAAAA
10  Q44  RTV   Y04937  0403030D0AAAAAA
11  Q44  RTV   Y04937  0403030D0AAABAB
12  Q44  RTV   Y04937  0403030P0AAAGAG
```

```
13  Q44  RTV   Y04937  0403030P0AAAKAK

                                     bnf_name  items    nic  act_cost  \
9   Trazodone HCl_Cap 50mg                         1   1.19      1.22
10  Citalopram Hydrob_Tab 20mg                     1   1.17      1.20
11  Citalopram Hydrob_Tab 10mg                     1   0.76      0.82
12  Paroxetine HCl_Oral Soln 10mg/5ml S/F          1  15.99     14.94
13  Paroxetine HCl_Tab 10mg                        1  16.50     15.41

    quantity  period
9         14  201804
10        14  201804
11        14  201804
12       263  201804
13        49  201804
```

In [56]:
```python
#Total number of prescription
antide.quantity.sum()
```

Out[56]:
```
214223401
```

The total number of Antidepressants prescription is 214223401.

In [57]:
```python
antide.act_cost.sum()
```

Out[57]:
```
16853470.86
```

The total number of Antidepressants prescription is 16853470.86.

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

In [24]:
```python
#visualize the monthly total spending per registered patients using a scatterplot and
#Calcualte total costs for eachh practice

total_costs_practices =pd.DataFrame(PDPI.groupby(PDPI.practice).apply(lambda subf: su
total_costs_practices.columns = ['total_costs_per_practice']
# Reseting the index
total_costs_practices.reset_index(inplace=True)
total_costs_practices.head()
```

Out[24]:

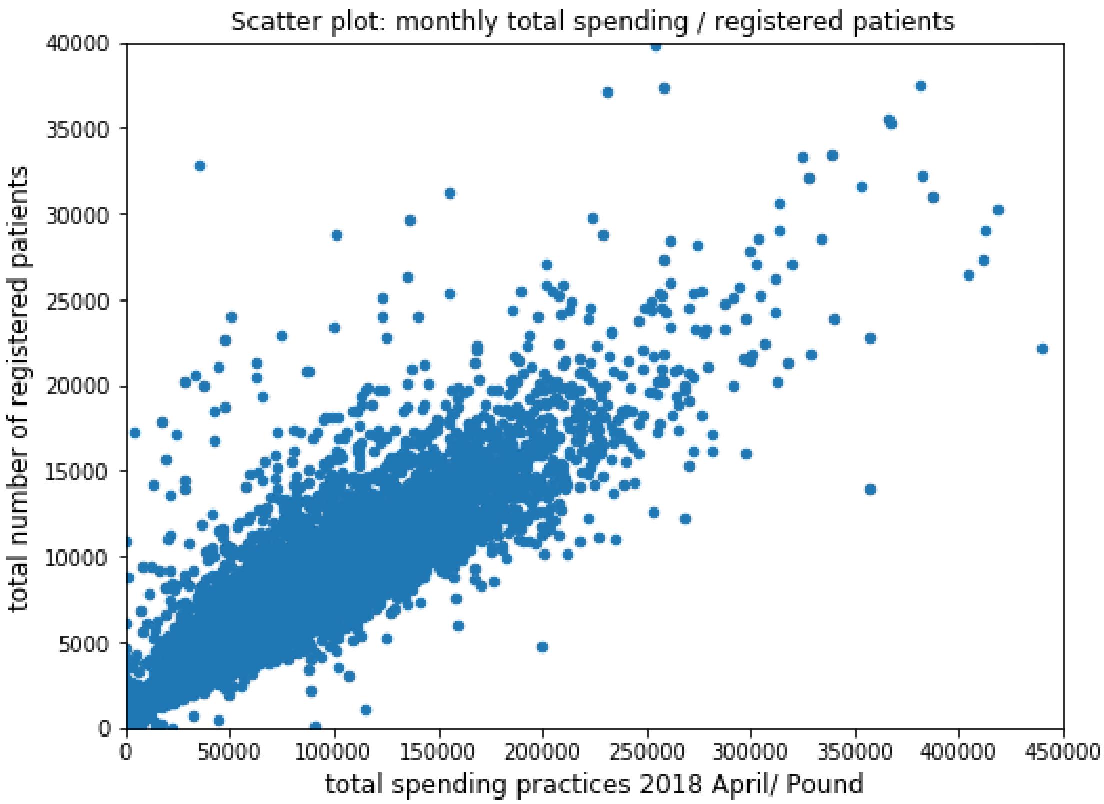
	practice	total_costs_per_practice
0	A81001	52194.63
1	A81002	268607.26
2	A81004	139115.40
3	A81005	102914.06
4	A81006	183226.79

In [25]:
```
gp_counts = pd.read_csv('/Users/charles/Desktop/gp-reg-pat-prac-all.csv').rename(colu
gp_counts.head()
```

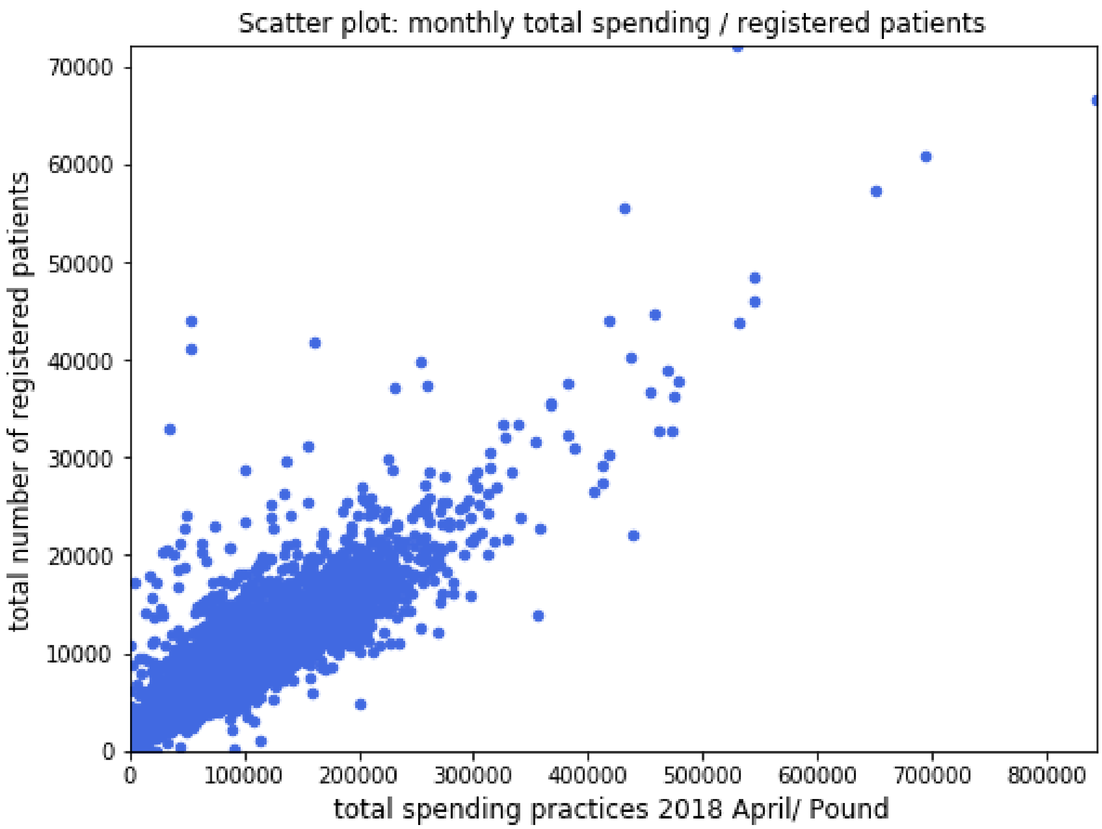
Out[25]:
```
        PUBLICATION EXTRACT_DATE TYPE CCG_CODE ONS_CCG_CODE    CODE POSTCODE  \
0  GP_PRAC_PAT_LIST    01APR2018   GP      00C    E38000042  A83005  DL1 3RT
1  GP_PRAC_PAT_LIST    01APR2018   GP      00C    E38000042  A83006  DL3 6HZ
2  GP_PRAC_PAT_LIST    01APR2018   GP      00C    E38000042  A83010  DL3 9JP
3  GP_PRAC_PAT_LIST    01APR2018   GP      00C    E38000042  A83013  DL1 4YL
4  GP_PRAC_PAT_LIST    01APR2018   GP      00C    E38000042  A83031  DL3 8SQ

   SEX  AGE  NUMBER_OF_PATIENTS
0  ALL  ALL               11826
1  ALL  ALL                8044
2  ALL  ALL               14070
3  ALL  ALL               11298
4  ALL  ALL               10109
```

In [26]:
```
#Merge two datasets by common key(practice and CODE)
#visualization by scatterplot, x-axis is total_cost_per_GP,
#y-axis is total number of registered patients_per_GP

merged = pd.merge(total_costs_practices, gp_counts[['CODE', 'NUMBER_OF_PATIENTS']], le
ax3=merged.plot(kind='scatter', x='total_costs_per_practice', y='NUMBER_OF_PATIENTS',
ax3.set_xlabel("total spending practices 2018 April/ Pound",fontsize=12)
ax3.set_ylabel("total number of registered patients",fontsize=12)
ax3.set_xlim(0, 450000)
ax3.set_ylim(0, 40000)
```

Out[26]:
```
(0, 40000)
```




```
In [27]: #Redraw the previous scatterplot and modify the max-value of x and y-axisű

         from math import floor
         max_x = floor(merged.total_costs_per_practice.max())
         max_y = floor(merged.NUMBER_OF_PATIENTS.max())

         ax4=merged.plot(kind='scatter', x='total_costs_per_practice', y='NUMBER_OF_PATIENTS',
                         color='royalblue', figsize=(8,6))
         ax4.set_xlabel("total spending practices 2018 April/ Pound",fontsize=12)
         ax4.set_ylabel("total number of registered patients",fontsize=12)
         ax4.set_xlim(0, max_x)
         ax4.set_ylim(0, max_y)

Out[27]: (0, 72227)
```

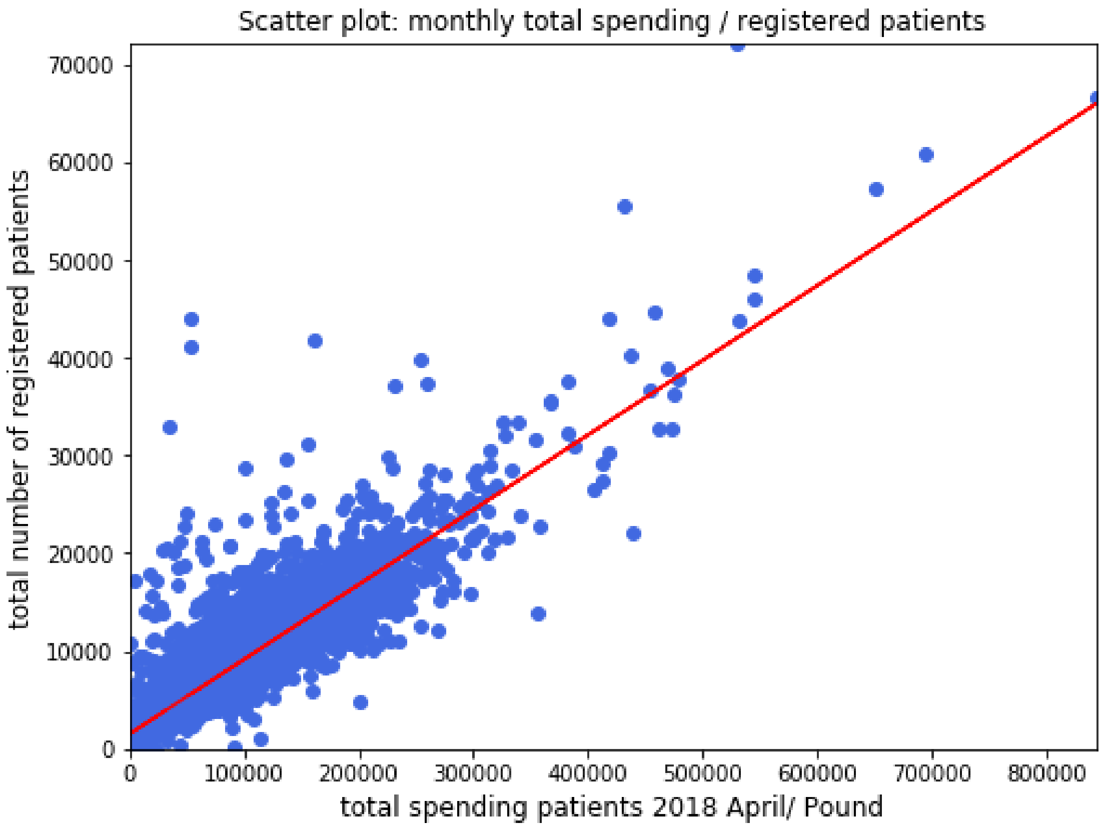


From the figure above, we can assume there is an linear correlation between total number of registered patients and monlthly total spending per practise. we will use python to simulate and validate the linear regression, calculate linear equation.

```
In [28]: #Scatterplot with correlation
         #plot those data points
         #fig, ax = plt.subplots()

         import matplotlib.pyplot as plt
         fig=plt.figure(figsize=(8, 6))
         ax=fig.add_subplot(111)
         x= merged['total_costs_per_practice']
         y = merged['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("total spending patients 2018 April/ Pound",fontsize=12)
         ax.set_ylabel("total number of registered patients",fontsize=12)
         max_x = floor(merged.total_costs_per_practice.max())
         max_y = floor(merged.NUMBER_OF_PATIENTS.max())
```

```
    ax.set_xlim(0, max_x)
    ax.set_ylim(0, max_y)
```

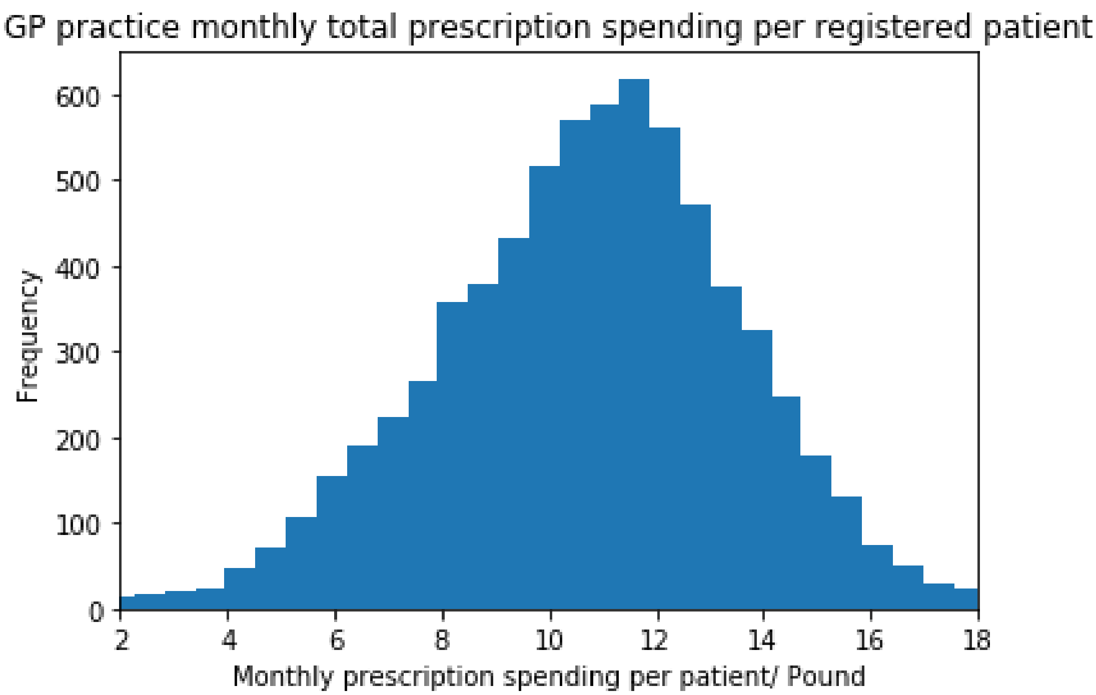
Out[28]: (0, 72227)



From the simulation, we get the linear equation y = 0.077*x +1485.56 (x:total spending practises April/pound,y: total number of registered patients). So from the equation, we can predict how many patients can a GP prescribe within a certain budget. Moreover, we can generate a histogram for relative spending for all practices and fit in Gaussian curve to identify the distribution of patients and monthly prescription spending per patient.

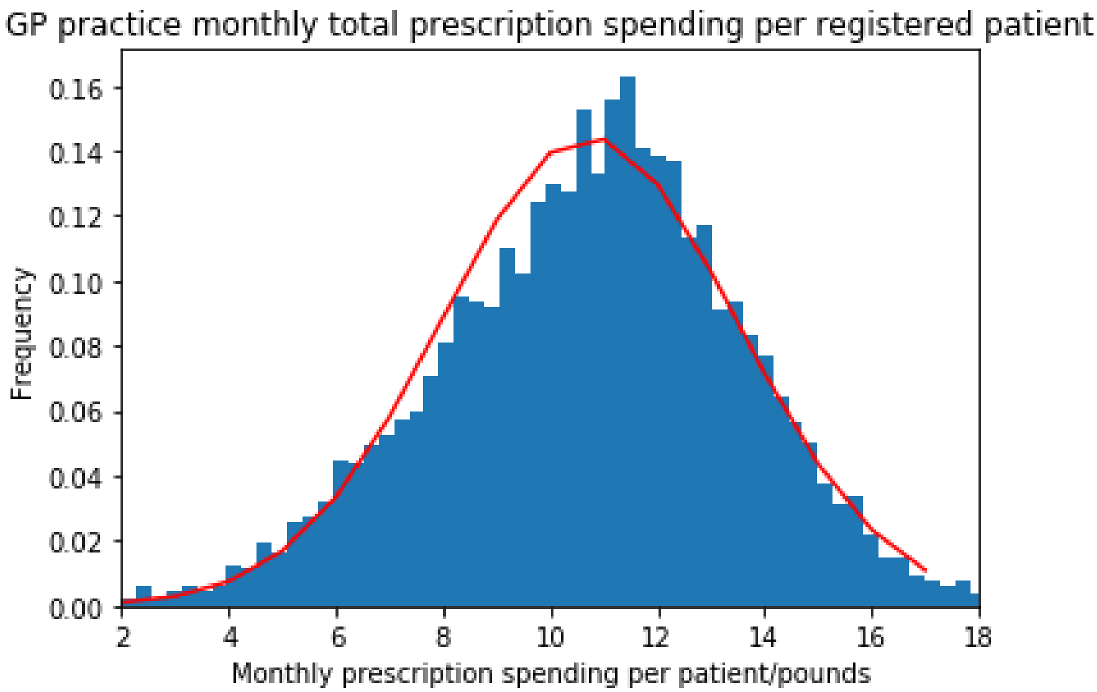
```
In [29]: #generate a histogram for relative spending for all practices and fit a Gaussian(norm

    cost_patient_plot = merged
    cost_patient_plot['cost_per_patient'] = cost_patient_plot['total_costs_per_practice']

    x = cost_patient_plot.cost_per_patient.values

    plt.hist(x, bins=5000)
    plt.xlabel("Monthly prescription spending per patient/ Pound")
    plt.ylabel("Frequency")
```

```
min_x = floor(cost_patient_plot['cost_per_patient'].quantile(.01))
max_x = floor(cost_patient_plot['cost_per_patient'].quantile(.99))
plt.xlim(min_x, max_x) #do not show outliers
plt.title("GP practice monthly total prescription spending per registered patient")
plt.show()
```




```
In [30]: from scipy.stats import norm


         cost_patient_plot = merged
         cost_patient_plot['cost_per_patient'] = cost_patient_plot['total_costs_per_practice']

         x = cost_patient_plot.cost_per_patient.values

         min_x = floor(cost_patient_plot['cost_per_patient'].quantile(.01))
         max_x = floor(cost_patient_plot['cost_per_patient'].quantile(.99))
         x2 =  cost_patient_plot[(x > min_x)&(x<max_x)]['cost_per_patient'] #some data are out
         rangea = np.arange(min_x,max_x,1)

         plt.hist(x, bins=10000,normed = True)
         plt.plot(rangea,norm.pdf(rangea,np.mean(x2),np.std(x2)),color = 'r') #fit in normal c

         plt.xlabel("Monthly prescription spending per patient/pounds")
         plt.ylabel("Frequency")
```

```python
plt.xlim(min_x, max_x) #do not show outliers
plt.title("GP practice monthly total prescription spending per registered patient")
plt.show()
```



From the figure above, we can see that the data mainly obey Gaussain distribution (mean is 10.73,std is 2.76) although slightly skewed. 95% of the patients are in distribution of spending 5.5 to 16.5 pounds per month (-2std to 2std), patients are more likely paying 8-14 pounds per month generally.

7 Assignment B

Background and Aim

The WHO Mortality Database is a database of registered deaths compiled by WHO from data given by national authorities around the world. The cause of each death is classified by the circumstances that led to death. The database contains number of deaths by country, year, sex, age group and cause of death as far back from 1950. In the datasets, we use ICD-10 code for recording the cause of death. Each country in the database is uniquely identified all WHO datasets by a four digit numeric code. The mapping between countries and identifier codes is located in the "Country codes" lookup file. Information on the population of each country is found in the "Population and live births" file.

Datasets: 1. Morticd10_part1.csv 2. Morticd10_part2.csv

Necessary Variables Explanation: Country : Country code Year : Year to which data refer Cause : Cause of death Deaths1 : Deaths at all ages Deaths2 : Deaths at age 0 year Deaths3 :

Deaths at age 1 year ... Deaths8 : Deaths at age 10-14 year ... Deaths24: Deaths at age 90-95 year Deaths25: Deaths at age 95 and above Deaths26: unspecified

3. pop.csv

Necessary Variables Explanation: Country : Country code Year : Year to which data refer Pop1 : Population at all ages Pop2 : Population at 0 years ... Pop7 :Population at age 5-9 years ... Pop24 :Population at age 90-94 years Pop25 :Population at age 95 years and over Pop26 :unspecified

8 Question1 What was the population and the total number of deaths (from all causes, all ages) in 2010 for:

o Iceland
o Italy
o New Zealand

```
In [31]: #First of all, Merge Morticd10_part1 and Morticd10_part2 into one dataset 'new_files'

         file1 = pd.read_csv('Morticd10_part1.csv')
         file2 = pd.read_csv('Morticd10_part2.csv')
         frames = [file1,file2]
         new_files = pd.concat(frames)
         new_files.head()
```

```
/Users/charles/anaconda3/lib/python3.6/site-packages/IPython/core/interactiveshell.py:2728: Dty
  interactivity=interactivity, compiler=compiler, result=result)
/Users/charles/anaconda3/lib/python3.6/site-packages/IPython/core/interactiveshell.py:2728: Dty
  interactivity=interactivity, compiler=compiler, result=result)
```

```
Out[31]:    Country  Admin1 SubDiv  Year  List  Cause  Sex  Frmat  IM_Frmat  Deaths1  \
         0     1400     NaN    NaN  2001   101   1000    1      7         8      332
         1     1400     NaN    NaN  2001   101   1000    2      7         8      222
         2     1400     NaN    NaN  2001   101   1001    1      7         8       24
         3     1400     NaN    NaN  2001   101   1001    2      7         8       14
         4     1400     NaN    NaN  2001   101   1002    1      7         8        0

               ...    Deaths21  Deaths22  Deaths23  Deaths24  Deaths25  Deaths26  \
         0     ...        95.0       NaN       NaN       NaN       NaN       0.0
         1     ...       112.0       NaN       NaN       NaN       NaN       0.0
         2     ...         5.0       NaN       NaN       NaN       NaN       0.0
         3     ...         6.0       NaN       NaN       NaN       NaN       0.0
         4     ...         0.0       NaN       NaN       NaN       NaN       0.0

            IM_Deaths1  IM_Deaths2  IM_Deaths3  IM_Deaths4
         0         8.0         NaN         NaN         NaN
         1        11.0         NaN         NaN         NaN
         2         0.0         NaN         NaN         NaN
```

```
3          0.0          NaN          NaN          NaN
4          0.0          NaN          NaN          NaN

[5 rows x 39 columns]
```

9 Mortality

The first question aims to know the total deaths(from all causes,all ages)and population in 2010 for Iceland, Italy and New Zealand. We will extract total number of death and population from two relevant datasets. From the documentation, we find the country codes for Iceland,Italy and New Zealand are 4160,4180 and 5150.

In [32]:
```
#oIceland 4160       o New Zealand 5150
#Total number of deaths Iceland (all cause,all age in 2010)

Total_deaths_Iceland = new_files.loc[(new_files['Country']==4160) & (new_files['Year']
Total_deaths_Iceland.Deaths1.sum()
```

Out[32]: 4038

The total number of deaths Iceland in 2010 is 4038.

In [33]:
```
#oItaly 4180
#Total number of deaths Italy (all cause,all age in 2010)

Total_deaths_Italy = new_files.loc[(new_files['Country']==4180) & (new_files['Year']==
Total_deaths_Italy.Deaths1.sum()
```

Out[33]: 1169230

The total number of deaths Italy in 2010 is 1169230.

In [34]:
```
#oItaly 5150
#Total number of deaths New Zealand (all cause,all age in 2010)

Total_deaths_Newzealand = new_files.loc[(new_files['Country']==5150) & (new_files['Yea
Total_deaths_Newzealand.Deaths1.sum()
```

Out[34]: 57298

The total number of deaths Italy in 2010 is 1169230.

10 Population

In [35]:
```
#read population csv
pop = pd.read_csv('pop.csv')
pop.head()
```

```
Out[35]:    Country  Admin1 SubDiv  Year  Sex  Frmat       Pop1      Pop2      Pop3  \
         0     1060     NaN    NaN  1980    1      7   137100.0    3400.0   15800.0
         1     1060     NaN    NaN  1980    2      7   159000.0    4000.0   18400.0
         2     1125     NaN    NaN  1955    1      2  5051500.0  150300.0  543400.0
         3     1125     NaN    NaN  1955    2      2  5049400.0  145200.0  551000.0
         4     1125     NaN    NaN  1956    1      2  5353700.0  158700.0  576600.0

            Pop4    ...         Pop18    Pop19    Pop20    Pop21    Pop22    Pop23  \
         0   NaN    ...           NaN   5300.0      NaN   2900.0      NaN      NaN
         1   NaN    ...           NaN   6200.0      NaN   3400.0      NaN      NaN
         2   NaN    ...      110200.0  51100.0  41600.0  14300.0  11800.0  25300.0
         3   NaN    ...      122100.0  51100.0  50700.0  15800.0  18000.0  28500.0
         4   NaN    ...      116900.0  54100.0  44000.0  14900.0  12400.0  26600.0

            Pop24  Pop25   Pop26        Lb
         0    NaN    NaN  6500.0    5000.0
         1    NaN    NaN  7500.0    6000.0
         2    NaN    NaN     0.0  253329.0
         3    NaN    NaN     0.0  237901.0
         4    NaN    NaN     0.0  250022.0

         [5 rows x 33 columns]
```

```
In [36]: # Pop1          Population at all ages
         # oIceland 4160

         pop_Iceland =pop.loc[(pop['Country']==4160)&(pop['Year']==2010)].Pop1.sum()
         pop_Iceland
```

```
Out[36]: 318041.0
```

The Population of Iceland in 2010 is 318041.

```
In [37]: #oItaly 4180

         pop_Italy =pop.loc[(pop['Country']==4180)&(pop['Year']==2010)].Pop1.sum()
         pop_Italy
```

```
Out[37]: 60483386.0
```

The Population of Italy in 2010 is 60483386.

```
In [38]: #o New Zealand 5150

         pop_Newzealand =pop.loc[(pop['Country']==5150)&(pop['Year']==2010)].Pop1.sum()
         pop_Newzealand
```

```
Out[38]: 4367360.0
```

The Population of Italy in 2010 is 4367360.

From the results above, the populations of Iceland, Italy and New Zealand are 318041,60483386 and 4367360. The mortality of these three countries are 4038,1169230,57298. The population differences are quite huge, the population of Italy is Iceland 190 times and the differences of deaths are also obvious. However, If we calculate the proportions of mortality/populations are 1.27%,1.93%,1.31% respectively, the mortaliy maintain 1% to 2% percentage of country population.

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

o Visualise the results using a histogram.

In the question2, in order to visualise the distribution of deaths by age group in Italy, we need to calculate total number of deaths according to different age groups.

In [39]:
```
#Total number of deaths Italy (all cause,all age)

Total_deaths_Italy = new_files.loc[(new_files['Country']==4180)]
Total_deaths_Italy.Deaths1.sum()
```

Out[39]:
```
15280766
```

In [40]:
```
# rename age_group by real age groups and rebuild deaths dataframe according to age g

age_group = ['Deaths2','Deaths3','Deaths4','Deaths5','Deaths6','Deaths7','Deaths8','De
             'Deaths12','Deaths13','Deaths14','Deaths15','Deaths16','Deaths17','Death
             'Deaths22','Deaths23','Deaths24','Deaths25','Deaths26','IM_Deaths1','IM_
            ]
list1 = []
for i in age_group:
    list1.append(Total_deaths_Italy[i].sum())

Death_age = ['0','1','2','3','4','5-9','10-14','15-19','20-24','25-29','30-34','35-39
Italy_Death_age = zip(Death_age,list1)
data_dict = dict(Italy_Death_age)
Deaths = pd.DataFrame(list(data_dict.items()), columns=['all_age', 'Deaths'])
Deaths.head()
```

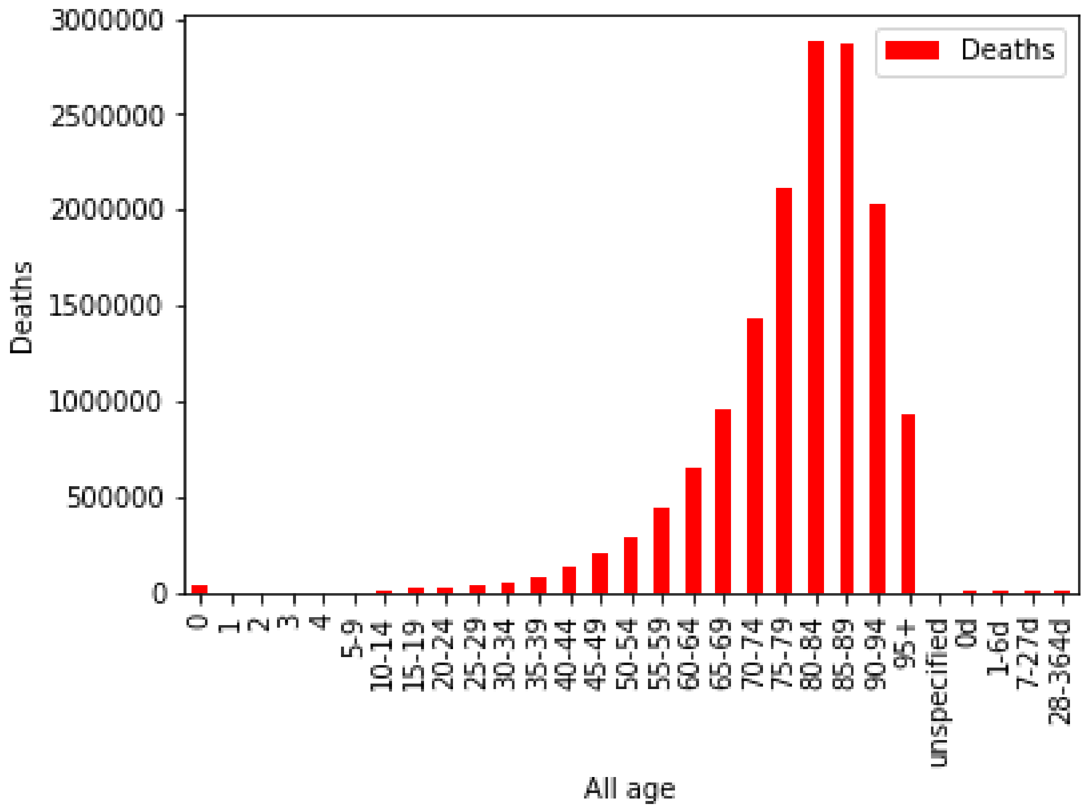
Out[40]:

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

In [41]:
```
#Visualisation

ax = Deaths[['all_age','Deaths']].plot(kind ='bar',x ='all_age',y='Deaths',color = 'r
```

```
ax.set_xlabel("All age",fontsize=10)

ax.set_ylabel("Deaths",fontsize=10)
```

Out[41]: Text(0,0.5,'Deaths')



From the figure above, we can see that Deaths of age in Italy 80-84 and 85-89 are highest, almost the same amount. The following four ranks are 75-79,90-94,70-74 and 95+. On the other hand, the age less than 60 years old have obviously low deaths.The deaths keeps quadraticly increasing from young to 89. However, age less than 1 years old, which mean the new babies having a relatively high deaths. Italian health authorities need to pay more efforts in improving medical conditions at new babies and the aged people (more than 70).

12 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)?

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

o Generate a pie chart to visualize the proportion of deaths.

In [42]:
```
Total_deaths_Italy = new_files.loc[(new_files['Country']==4180)]
```

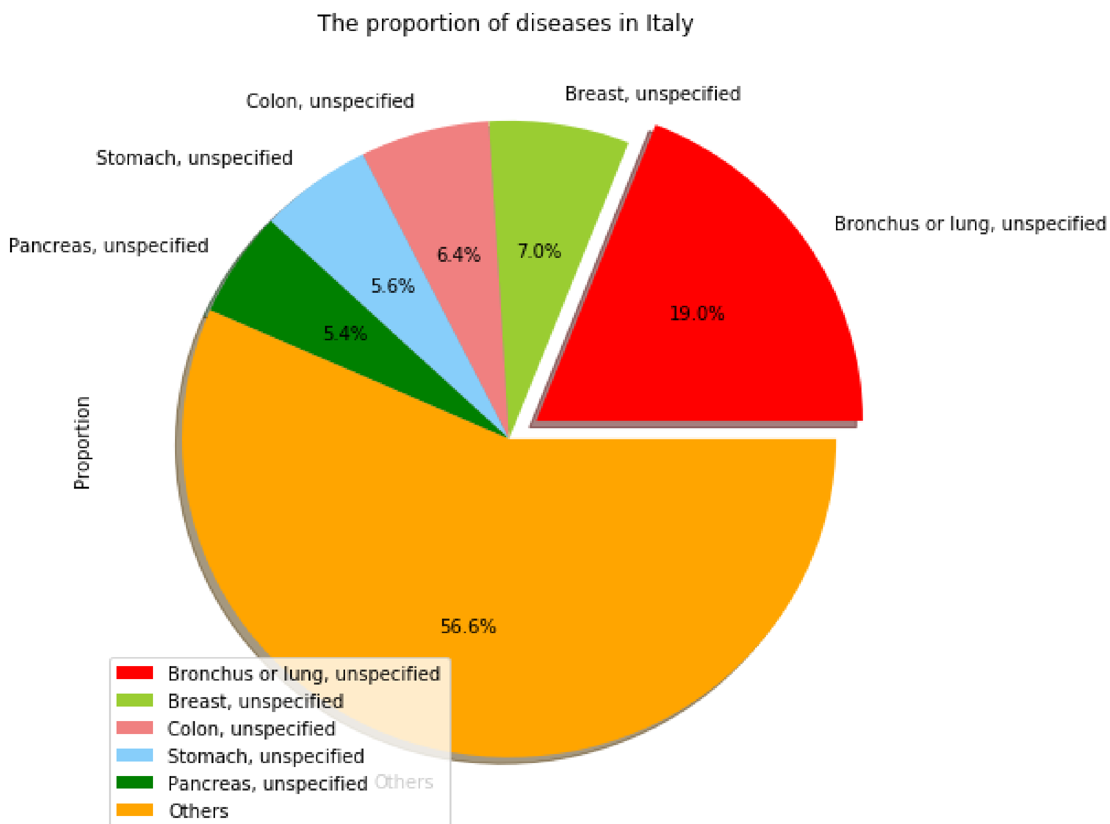
```
codelist = (Total_deaths_Italy.Cause > 'C00')&(Total_deaths_Italy.Cause < 'D48')
new_causelist = Total_deaths_Italy[codelist].Cause.values
##CH02        C00-D48        NEOPLASMS
Italy_dneoplasms = Total_deaths_Italy.loc[Total_deaths_Italy.Cause.isin(new_causelist)
Italy_dneoplasms_groupby =Italy_dneoplasms.groupby('Cause').sum()

# Generate a table with the cause of death, the number of deaths, and the proportion

Italy_dneoplasms_Deaths =pd.DataFrame(Italy_dneoplasms_groupby['Deaths1'])
Italy_dneoplasms_SortedDeaths =Italy_dneoplasms_Deaths.sort_values('Deaths1', axis=0,
Italy_dneoplasms_SortedDeaths.head()
Italy_dneoplasms_SortedDeaths['Proportion'] =  Italy_dneoplasms_SortedDeaths['Deaths1
Italy_dneoplasms_SortedDeaths.head()
```

Out[42]:

Cause	Deaths1	Proportion
C349	426451	0.190419
C509	155895	0.069610
C189	143188	0.063936
C169	125679	0.056118
C259	120070	0.053614

In [43]:
```
# Visualise top five diseases
new_Italy_dneoplasms_SortedDeaths = Italy_dneoplasms_SortedDeaths[:5]

#separate top five diseases and other diseases
other_proportion =1-new_Italy_dneoplasms_SortedDeaths.Proportion.sum()
new_Italy_dneoplasms_SortedDeaths.loc['others'] = other_proportion

# Generate a pie chart to visualize the proportion of deaths.

labels = 'Bronchus or lung, unspecified', 'Breast, unspecified', 'Colon, unspecified'
explode = (0.1, 0, 0, 0, 0 ,0)
colors = ['red', 'yellowgreen', 'lightcoral', 'lightskyblue','green','orange']

titles="The proportion of diseases in Italy "
plot = new_Italy_dneoplasms_SortedDeaths.plot.pie(y='Proportion',explode=explode, fig
```

```
/Users/charles/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:6: SettingWithCopyWa
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html
```



From the pie chart above, we can see that the neoplasms of bronchus or lung are taking highest proportion of deaths,19.0% of entire deaths. The followings fours are breast neoplasms(7.0%), colon neoplasms(6.4%), stomach neoplasms(5.6%) and pancreas neoplasms(5.4%). Bronchus or lung cancer is caused by enviroment and living habits, such as smoking. We found some information on the epidemiology website (https://www.statista.com/statistics/802436/number-of-lung-cancer-cases-by-gender-in-italy/) show that the smoking people in Italy keep increasing from 2010 to 2015, both males and females. This might be considered as lung cancer ranking first evidence. It is quite interesting that we combine colon and stomach neoplasms as a part (12% of entire deaths). High proportion of colon and stomack neoplasms indicates that the foods or drinks might assocaite with cancer. Such as Pizza, cake,cheese are containing high carbo,fat,sugar and salt. Insufficient intaking of fibre and vitamins is unhealthy to digestive system. And drinking alcohol heavily and expresso coffee also increase digestive burden.

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

```
In [123]: #Total number of deaths from Neoplasms Australia for 2010
          Total_deaths_Australia = new_files.loc[(new_files['Country']==5020)&(new_files['Year
          Australia_dneoplasms = Total_deaths_Australia.loc[Total_deaths_Australia.Cause.isin(
          Australia_dneoplasms.head()
```

```
Out[123]:          Country  Admin1 SubDiv  Year List Cause  Sex  Frmat  IM_Frmat  \
        2144494     5020     NaN    NaN  2010  104  C001    1      0         1
        2144495     5020     NaN    NaN  2010  104  C001    2      0         1
        2144496     5020     NaN    NaN  2010  104  C009    1      0         1
        2144497     5020     NaN    NaN  2010  104  C009    2      0         1
        2144498     5020     NaN    NaN  2010  104   C01    1      0         1

                 Deaths1     ...      Deaths21  Deaths22  Deaths23  Deaths24  \
        2144494        2     ...           0.0       1.0       0.0       0.0
        2144495        2     ...           0.0       1.0       0.0       0.0
        2144496        2     ...           0.0       1.0       0.0       0.0
        2144497        5     ...           2.0       0.0       0.0       1.0
        2144498       20     ...           3.0       0.0       0.0       0.0

                 Deaths25  Deaths26  IM_Deaths1  IM_Deaths2  IM_Deaths3  IM_Deaths4
        2144494       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
        2144496       0.0       0.0         0.0         0.0         0.0         0.0
        2144497       1.0       0.0         0.0         0.0         0.0         0.0
        2144498       0.0       0.0         0.0         0.0         0.0         0.0

        [5 rows x 39 columns]
```

```
In [129]: #Top five age groups in Australia dying with a Neoplasms cause of death

          list3 = []
          for i in age_group:
              list3.append(Australia_dneoplasms[i].sum())

          Australia_dneoplasms_Death_age = zip(Death_age,list3)
          data_dict2 = dict(Australia_dneoplasms_Death_age)

          Dneoplasms_Deaths_Australia = pd.DataFrame(list(data_dict2.items()), columns=['all_ag

          Sorted_Dneoplasms_Deaths_Australia = Dneoplasms_Deaths_Australia.sort_values('Deaths
          Sorted_Dneoplasms_Deaths_Australia.all_age.head(5)
```

```
Out[129]: 20    80-84
          19    75-79
          18    70-74
          21    85-89
          17    65-69
          Name: all_age, dtype: object
```

Top five age groups in Australia dying with a Neoplasms cause of death are 80-84,75-79,70-74,85-89 and 65-69. From the age groups, we assume that people over 65 years old are likely to get neoplasms.

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

In [130]:
```
# Combine information on the population and deaths and describe your logic.
#total population of Italy
pop_Italy_2010 =pop.loc[(pop['Country']==4180)&(pop['Year']==2010)].Pop1.sum()
pop_Italy_2010
```

Out[130]: 60483386.0

In [131]:
```
pop_Australia_2010 =pop.loc[(pop['Country']==5020)&(pop['Year']==2010)].Pop1.sum()
pop_Australia_2010
```

Out[131]: 22297515.0

In [132]:
```
#Total number of deaths from Neoplasms Italy for 2010

Total_deaths_Italy = new_files.loc[(new_files['Country']==4180)&(new_files['Year']==2
Italy_dneoplasms = Total_deaths_Italy.loc[Total_deaths_Italy.Cause.isin(new_causelist
Italy_dneoplasms_groupby = Italy_dneoplasms.groupby('Cause').sum()
Italy_dneoplasms = pd.DataFrame(Italy_dneoplasms_groupby.Deaths1)
Italy_dneoplasms['It_frequency_per1000000'] = Italy_dneoplasms.Deaths1*100000/pop_Ita
Italy_dneoplasms.columns=['It_Deaths', 'It_frequency_per100000']
Italy_dneoplasms.head()
```

Out[132]:

Cause	It_Deaths	It_frequency_per100000
C000	7	0.011573
C001	27	0.044640
C006	1	0.001653
C009	31	0.051254
C01	95	0.157068

In [133]:
```
#Total number of deaths from Neoplasms Australia for 2010

Total_deaths_Australia = new_files.loc[(new_files['Country']==5020)&(new_files['Year
Australia_dneoplasms = Total_deaths_Australia.loc[Total_deaths_Australia.Cause.isin(n
Australia_dneoplasms_groupby = Australia_dneoplasms.groupby('Cause').sum()
Australia_dneoplasms = pd.DataFrame(Australia_dneoplasms_groupby.Deaths1)
Australia_dneoplasms['Au_frequency_per100000'] = Australia_dneoplasms.Deaths1*100000/
Australia_dneoplasms.columns=['Au_Deaths', 'Au_frequency_per100000']
Australia_dneoplasms.head()
```

Out[133]:

Cause	Au_Deaths	Au_frequency_per100000
C001	4	0.017939
C009	7	0.031394
C01	27	0.121090
C020	1	0.004485
C028	2	0.008970

```
In [134]: Australia_dneoplasms['Au_Deaths'].sum()
```

```
Out[134]: 43275
```

```
In [139]: #Combine Italy and Australia Deaths table together and list top5 deaths frequency pe

          Deaths_compare =Italy_dneoplasms.join(Australia_dneoplasms,how = 'outer')
          Au_Sorted_death_compare = Deaths_compare.sort_values('Au_frequency_per100000',ascendi
          Au_Sorted_death_compare_Top5 =Au_Sorted_death_compare[:5]
          Au_Sorted_death_compare_Top5
```

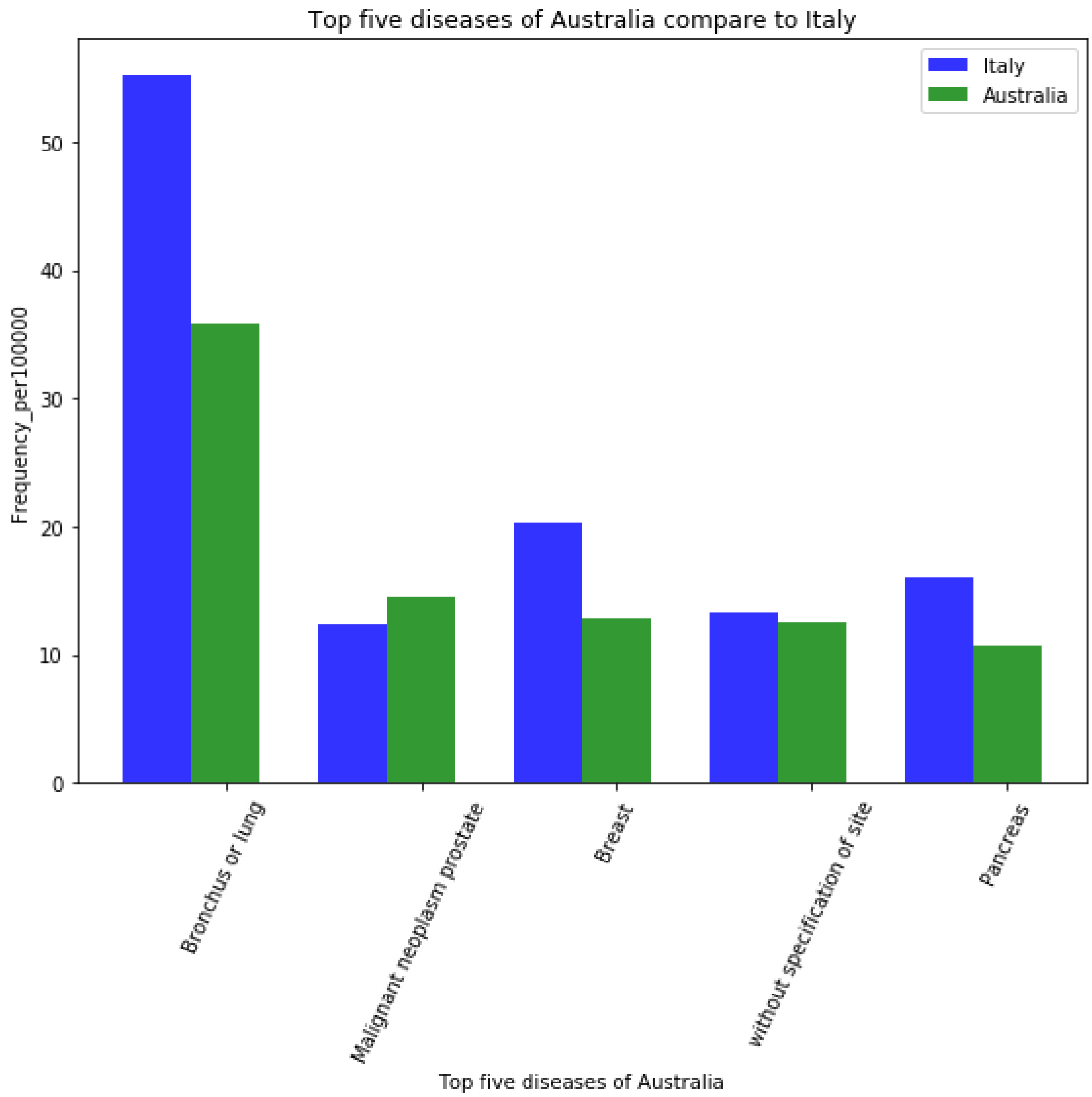
Out[139]:

Cause	It_Deaths	It_frequency_per100000	Au_Deaths	Au_frequency_per100000
C349	33416.0	55.248230	7989.0	35.829105
C61	7509.0	12.414980	3236.0	14.512828
C509	12231.0	20.222082	2865.0	12.848965
C809	8036.0	13.286293	2783.0	12.481211
C259	9683.0	16.009355	2367.0	10.615533

We calculate frequency of deaths per 100000 people by Neoplasms in Italy and Australia in 2010. Using the formula deaths * 100000/population and list top 5 causes according Austrlia deaths freaquency per 100000.

```
In [53]: #Compare top five Neoplasms of Australia deaths frequency per 10000 with Italy

         Au_Top5 = Au_Sorted_death_compare_Top5.Au_frequency_per100000
         Au_au_Top5 =list(Au_Top5.values)
         It_Top5 = Au_Sorted_death_compare_Top5.It_frequency_per100000
         It_au_top5 =list(It_Top5.values)

         # data to plot
         n_groups = 5

         # create plot
         fig, ax = plt.subplots(figsize =(8,8))
         index = np.arange(n_groups)
         bar_width = 0.35
         opacity = 0.8

         rects1 = plt.bar(index, It_au_top5, bar_width,
                          alpha=opacity,
                          color='b',
                          label='Italy')

         rects2 = plt.bar(index + bar_width, Au_au_Top5, bar_width,
                          alpha=opacity,
                          color='g',
                          label='Australia')
```

```
plt.xlabel('Top five diseases of Australia')
plt.ylabel('Frequency_per100000')
plt.title('Top five diseases of Australia compare to Italy')
plt.xticks(index + bar_width, ('Bronchus or lung', 'Malignant neoplasm prostate', 'Bre
plt.legend()
plt.tight_layout()
plt.show()
```



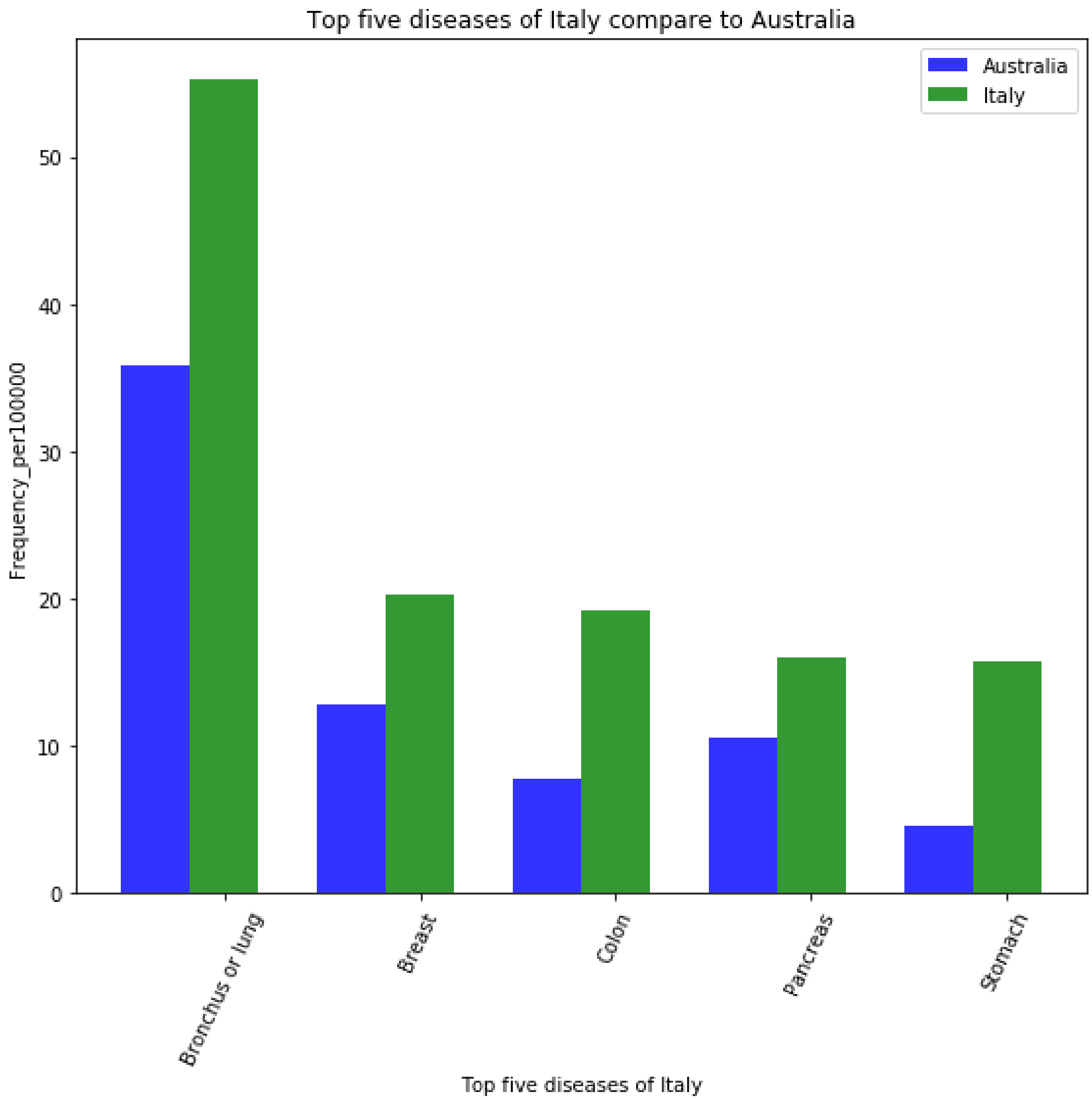
From the figure of Top five diseases of Austalia, we can see that neoplasm of bronchus or lung is the highest. The followings are malignant neoplasm prostate, breast, without specification of site and pancreas. On the other side, the blue chart is Italy, Italy has a higher frequency than in neoplasms of bronchus, breast and pancreas. almost same percentage of neoplasms of without specification of site and less frequency of malignant neoplasm prostate.

In [54]:
```
#Compare top five Neoplasms of Italy deaths frequency per 10000 with Australia

It_Sorted_death_compare = Deaths_compare.sort_values('It_frequency_per100000',ascendi
It_Sorted_death_compare_Top5 =It_Sorted_death_compare[:5]
It_Sorted_death_compare_Top5
```

Out[54]:

Cause	It_Deaths	It_frequency_per100000	Au_Deaths	Au_frequency_per100000
C349	33416.0	55.248230	7989.0	35.829105
C509	12231.0	20.222082	2865.0	12.848965
C189	11638.0	19.241648	1738.0	7.794591
C259	9683.0	16.009355	2367.0	10.615533
C169	9523.0	15.744820	1004.0	4.502744

In [55]:
```
#Compare top five Neoplasms of Italy deaths frequency per 10000 with Australia

Au_Top5 = It_Sorted_death_compare_Top5.Au_frequency_per100000
Au_it_Top5 =list(Au_Top5.values)
It_Top5 = It_Sorted_death_compare_Top5.It_frequency_per100000
It_it_Top5 =list(It_Top5.values)

# data to plot
n_groups = 5

# create plot
fig, ax = plt.subplots(figsize =(8,8))
index = np.arange(n_groups)
bar_width = 0.35
opacity = 0.8

rects1 = plt.bar(index, Au_it_Top5, bar_width,
                 alpha=opacity,
                 color='b',
                 label='Australia')

rects2 = plt.bar(index + bar_width, It_it_Top5, bar_width,
                 alpha=opacity,
                 color='g',
                 label='Italy')

plt.xlabel('Top five diseases of Italy')
plt.ylabel('Frequency_per100000')
plt.title('Top five diseases of Italy compare to Australia')
plt.xticks(index + bar_width, ('Bronchus or lung', 'Breast', 'Colon', 'Pancreas','Sto
plt.legend()
plt.tight_layout()
plt.show()
```



Similar as the figure of Top five diseases of Austalia, we can see that neoplasm of bronchus or lung is also the highest of Italy. The followings are breast,colon,pancreas and Stomach. As we have discussed above that one main reason of leading to bronchus or lung neoplasms is smoking, which in both Australia and Italy signidicantly. Unlike Italy, as we metioned that the foods and drinks increas digestive system in Italy and lead to colon and stomach eoplasms, Australia does not have high frequent deaths of colon and stomach neoplasms. We infer Australian have healthier life style and eating habits compare to Italian. However, both countries have high frequency of breast and pancreas neoplasms that should arouse the attention of relevant health authorities.