Candidate Number : BSYP1
Github link : https://github.com/bsyp1/assignment
Word count : 2497 (not including code, raw code output, tables, figures and headings thereof)

In [1]:
```
import pandas as pd
from pandasql import PandaSQL
pdsql = PandaSQL()
import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
from scipy.stats import norm
```

Assignment A

Overview

UK general practice prescribing data for April 2018 (at a presentation level, i.e. total number of items, total net and actual cost and total quantity) were downloaded from https://digital.nhs.uk/data-and-information/. In addition,linked practice detail, prescription detail and patient numbers (per practice) data were downloaded from the same website. From this data information about practices, their prescribing patterns, number and cost of prescriptions are described for London and Cambridge. In addition number and total cost across all practices nationally are described for cardiovascular and antidepressant prescriptions. Total and relative spending per patient nationally are also described.

0. Data checking and cleaning

In [2]:
```
#Read in raw data files for GP data

#presentation level practice prescriptions (rxs)
url = 'https://files.digital.nhs.uk/38/03EC1C/T201804PDPI%20BNFT.CSV'
practice_rxs = pd.read_csv(url)
practice_rxs.head()

#practice details
#by inspection of raw data, this file has no header info
cols = ['DATE','PRACTICE', 'PRACTICE_NAME', 'ADD1', 'ADD2','ADD3','ADD4',
'POSTCODE']
url = 'https://files.digital.nhs.uk/20/09E30B/T201804ADDR%20BNFT.CSV'
practice_details = pd.read_csv(url, names=cols)

#prescription details
#by inspection of raw data, problematic column name was altered in raw dat
a file (CHEM SUB -> CHEMSUB)
url = 'https://files.digital.nhs.uk/79/6D58A8/T201804CHEM%20SUBS.CSV'
rx_details = pd.read_csv(url)

#no. of patients per practice
```

```
url = 'https://files.digital.nhs.uk/71/B59D99/gp-reg-pat-prac-all.csv'
pats_per_practice = pd.read_csv(url)
```

In [3]:
```
#define a function to provide metadata on a given dataframe
def examine(df):
    print(df.shape)
    print(df.info(null_counts=True))
    print(df.describe(include=[np.number]).T)
    print(df.describe(include=[np.object, pd.Categorical]).T)
    return df.head()
```

In [4]:
```
#check practice_rxs
examine(practice_rxs)
```

```
(9748354, 11)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9748354 entries, 0 to 9748353
Data columns (total 11 columns):
 SHA                                                9748354 non-null object
PCT                                                9748354 non-null object
PRACTICE                                           9748354 non-null object
BNF CODE                                           9748354 non-null object
BNF NAME                                           9748354 non-null object
ITEMS                                              9748354 non-null int64
NIC                                                9748354 non-null float64
ACT COST                                           9748354 non-null float64
QUANTITY                                           9748354 non-null int64
PERIOD                                             9748354 non-null int64
                                                   9748354 non-null object
dtypes: float64(2), int64(3), object(6)
memory usage: 818.1+ MB
None
                count           mean          std       min        25%  \
ITEMS       9748354.0       9.115409    29.993817       0.0       1.00
NIC         9748354.0      70.782422   191.839958       0.0       7.92
ACT COST    9748354.0      65.979076   178.252617       0.0       7.46
QUANTITY    9748354.0     713.556001  4124.963843       0.0      28.00
PERIOD      9748354.0  201804.000000     0.000000  201804.0  201804.00

                  50%        75%         max
ITEMS            2.00       6.00     5147.00
NIC             22.50      62.86    33918.73
ACT COST        21.12      58.68    31455.94
QUANTITY        90.00     336.00  2281694.00
PERIOD      201804.00  201804.00   201804.00
                                                  count  unique   \
 SHA                                            9748354      27
PCT                                             9748354     397
PRACTICE                                        9748354    9578
BNF CODE                                        9748354   22358
BNF NAME                                        9748354   19227
                                                9748354       1


         top   \
 SHA
```

```
           Q46
PCT
           15E
PRACTICE
       M85063
BNF CODE                                                                   060
3020T0AAACAC
BNF NAME                                                 GlucoRX FinePoint Needles Pe
n Inj Screw



                                                      freq
 SHA                                                615496
PCT                                                 227462
PRACTICE                                              4003
BNF CODE                                              7964
BNF NAME                                             16287
                                                   9748354
```

Out[4]:

	SHA	PCT	PRACTICE	BNF CODE	BNF NAME	ITEMS	NIC	ACT COST	QUANTITY
0	Q44	RTV	Y04937	0401010Z0AAAAAA	Zopiclone_Tab 7.5mg	6	1.56	2.12	63
1	Q44	RTV	Y04937	0401020K0AAAHAH	Diazepam_Tab 2mg	4	0.87	1.15	73
2	Q44	RTV	Y04937	0401020K0AAAIAI	Diazepam_Tab 5mg	2	0.46	0.56	35
3	Q44	RTV	Y04937	0402010ABAAABAB	Quetiapine_Tab 25mg	1	2.60	2.52	14
4	Q44	RTV	Y04937	0402010ADAAAAAA	Aripiprazole_Tab 10mg	1	1.53	1.53	14

In [5]:

```
#tidy up prescription data

#get rid of spaces in column names
cols = practice_rxs.columns
print(cols)
cols = cols.map(lambda x: x.replace(' ', ''))
print(cols)
practice_rxs.columns = cols

#exclude blank 11th column
practice_rxs=practice_rxs[['SHA', 'PCT', 'PRACTICE', 'BNFCODE', 'BNFNAME',
 'ITEMS', 'NIC',
        'ACTCOST', 'QUANTITY', 'PERIOD']]

print(practice_rxs.shape)
practice_rxs.head()
```

```
Index([' SHA', 'PCT', 'PRACTICE', 'BNF CODE',
       'BNF NAME                                    ', 'ITEMS  ',
       'NIC        ', 'ACT COST   ', 'QUANTITY', 'PERIOD',
       '                   '],
      dtype='object')
Index(['SHA', 'PCT', 'PRACTICE', 'BNFCODE', 'BNFNAME', 'ITEMS', 'NIC',
       'ACTCOST', 'QUANTITY', 'PERIOD', ''],
      dtype='object')
(9748354, 10)
```

Out[5]:

	SHA	PCT	PRACTICE	BNFCODE	BNFNAME	ITEMS	NIC	ACTCOST	QUAN
0	Q44	RTV	Y04937	0401010Z0AAAAAA	Zopiclone_Tab 7.5mg	6	1.56	2.12	63
1	Q44	RTV	Y04937	0401020K0AAAHAH	Diazepam_Tab 2mg	4	0.87	1.15	73
2	Q44	RTV	Y04937	0401020K0AAAIAI	Diazepam_Tab 5mg	2	0.46	0.56	35
3	Q44	RTV	Y04937	0402010ABAAABAB	Quetiapine_Tab 25mg	1	2.60	2.52	14
4	Q44	RTV	Y04937	0402010ADAAAAAA	Aripiprazole_Tab 10mg	1	1.53	1.53	14

In [6]:

```
#check practice details
examine(practice_details)
```

```
(9578, 8)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 8 columns):
DATE             9578 non-null int64
PRACTICE         9578 non-null object
PRACTICE_NAME    9578 non-null object
ADD1             9578 non-null object
ADD2             9578 non-null object
ADD3             9578 non-null object
ADD4             9578 non-null object
POSTCODE         9578 non-null object
dtypes: int64(1), object(7)
memory usage: 598.7+ KB
None
       count       mean  std       min       25%       50%       75%
max
DATE  9578.0  201804.0  0.0  201804.0  201804.0  201804.0  201804.0  20180
4.0
              count unique                                  top  freq
PRACTICE       9578   9578                               G81027     1
PRACTICE_NAME  9578   9034  HIGH STREET SURGERY                     8
ADD1           9578   7771                 THE SURGERY            322
ADD2           9578   7233                                        688
ADD3           9578   2444                                        363
```

```
ADD4          9578    402                                  1918
POSTCODE      9578   7569                          SW20 8DA    20
```

Out[6]:

	DATE	PRACTICE	PRACTICE_NAME	ADD1	ADD2	ADD3	
0	201804	A81001	THE DENSHAM SURGERY	THE HEALTH CENTRE	LAWSON STREET	STOCKTON-ON-TEES	CLE
1	201804	A81002	QUEENS PARK MEDICAL CENTRE	QUEENS PARK MEDICAL CTR	FARRER STREET	STOCKTON ON TEES	CLE
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	CLE

In [7]:

```
#check prescription details
examine(rx_details)
```

```
(3496, 4)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3496 entries, 0 to 3495
Data columns (total 4 columns):
CHEM SUB                                                    3496 non-
null object
NAME                                                        3496 non-
null object
                                                  201804    3496 non-
null object
                                                            0 non-nul
l float64
dtypes: float64(1), object(3)
memory usage: 109.3+ KB
None
     count  mean  std  min  25%  50%  75%  max
       0.0   NaN  NaN  NaN  NaN  NaN  NaN  NaN
                                              count unique  \
CHEM SUB                                       3496   3496
NAME                                           3496   2987
                                         ...   3496      1



                        top   \
CHEM SUB
                   0504010AB
NAME                                          Ephedrine Hydrochlorid
e                       ...
```

```
                                                    ...


                                                          freq
CHEM SUB                                                     1
NAME                                                         8
                                                    ...   3496
```

Out[7]:

	CHEM SUB	NAME	201804	
0	0101010A0	Alexitol Sodium ...		NaN
1	0101010B0	Almasilate ...		NaN
2	0101010C0	Aluminium Hydroxide ...		NaN
3	0101010D0	Aluminium Hydroxide With Magnesium ...		NaN
4	0101010E0	Hydrotalcite ...		NaN

In [8]:

```
#tidy up prescription details data
pd.set_option('display.max_colwidth', -1)

#exclude blank column
cols=['CHEMSUB','DRUGNAME']
rx_details = rx_details.iloc[:,[0,1]]
rx_details.columns=cols

#data quality checks - 8 character codes and multiple values of lookup key
rx_details['len'] = rx_details['CHEMSUB'].str.len()
print(rx_details['len'].value_counts())
```

```
9    3496
Name: len, dtype: int64
```

In [9]:

```
#check practice details data
examine(pats_per_practice)
```

```
(7241, 10)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7241 entries, 0 to 7240
Data columns (total 10 columns):
PUBLICATION           7241 non-null object
EXTRACT_DATE          7241 non-null object
TYPE                  7241 non-null object
CCG_CODE              7241 non-null object
ONS_CCG_CODE          7241 non-null object
CODE                  7241 non-null object
POSTCODE              7241 non-null object
SEX                   7241 non-null object
AGE                   7241 non-null object
NUMBER_OF_PATIENTS    7241 non-null int64
dtypes: int64(1), object(9)
memory usage: 565.8+ KB
None
                     count          mean          std  min      25%      50%
 \
```

```
NUMBER_OF_PATIENTS  7241.0  8153.514017  5184.888435  1.0  4501.0  7235.0


                        75%      max
NUMBER_OF_PATIENTS  10711.0  72227.0
                 count unique                top  freq
PUBLICATION       7241     1    GP_PRAC_PAT_LIST  7241
EXTRACT_DATE      7241     1           01APR2018  7241
TYPE              7241     1                  GP  7241
CCG_CODE          7241   195                 15E   176
ONS_CCG_CODE      7241   195           E38000220   176
CODE              7241  7241              D81606     1
POSTCODE          7241  6530            SK11 6JL     7
SEX               7241     1                 ALL  7241
AGE               7241     1                 ALL  7241
```

Out[9]:

	PUBLICATION	EXTRACT_DATE	TYPE	CCG_CODE	ONS_CCG_CODE	CODE	PO
0	GP_PRAC_PAT_LIST	01APR2018	GP	00C	E38000042	A83005	DL1
1	GP_PRAC_PAT_LIST	01APR2018	GP	00C	E38000042	A83006	DL3
2	GP_PRAC_PAT_LIST	01APR2018	GP	00C	E38000042	A83010	DL3
3	GP_PRAC_PAT_LIST	01APR2018	GP	00C	E38000042	A83013	DL1
4	GP_PRAC_PAT_LIST	01APR2018	GP	00C	E38000042	A83031	DL3

In [10]:

```
#tidy up practice details data

#rename column to be consistent
pats_per_practice.rename(columns = {'CODE' :'PRACTICE'}, inplace=True)
pats_per_practice.head()
```

Out[10]:

	PUBLICATION	EXTRACT_DATE	TYPE	CCG_CODE	ONS_CCG_CODE	PRACTICE
0	GP_PRAC_PAT_LIST	01APR2018	GP	00C	E38000042	A83005
1	GP_PRAC_PAT_LIST	01APR2018	GP	00C	E38000042	A83006
2	GP_PRAC_PAT_LIST	01APR2018	GP	00C	E38000042	A83010
3	GP_PRAC_PAT_LIST	01APR2018	GP	00C	E38000042	A83013
4	GP_PRAC_PAT_LIST	01APR2018	GP	00C	E38000042	A83031

In [11]:

```
#merge prescriptions file with prescription details to get name of substan
ce

#get 9 digit code from BNFCODE column
practice_rxs['CHEMSUB'] = practice_rxs['BNFCODE'].str[0:9]
practice_rxs_sub = pd.merge(practice_rxs, rx_details, how='left', on='CHEM
SUB')
print(practice_rxs.shape)
print(practice_rxs_sub.shape)
```

```
practice_rxs_sub.head(5)
```

```
(9748354, 11)
(9748354, 13)
```

Out[11]:

	SHA	PCT	PRACTICE	BNFCODE	BNFNAME	ITEMS	NIC	ACTCOST	QUAN
0	Q44	RTV	Y04937	0401010Z0AAAAAA	Zopiclone_Tab 7.5mg	6	1.56	2.12	63
1	Q44	RTV	Y04937	0401020K0AAAHAH	Diazepam_Tab 2mg	4	0.87	1.15	73
2	Q44	RTV	Y04937	0401020K0AAAIAI	Diazepam_Tab 5mg	2	0.46	0.56	35
3	Q44	RTV	Y04937	0402010ABAAABAB	Quetiapine_Tab 25mg	1	2.60	2.52	14
4	Q44	RTV	Y04937	0402010ADAAAAAA	Aripiprazole_Tab 10mg	1	1.53	1.53	14

In [12]:

```
#check for missing substances
nosub = practice_rxs_sub[practice_rxs_sub['DRUGNAME'].isnull()]
nosub.head()
```

Out[12]:

	SHA	PCT	PRACTICE	BNFCODE	BNFNAME	ITEMS	NIC	ACTCOST	QUANTITY	P
191	Q44	RTV	Y05721	21010230111	Volumatic Paed + Mask	1	6.83	6.35	1	2(
192	Q44	RTV	Y05721	21220000236	Cetraben Crm 1050g	1	11.62	10.79	1	2(
543	Q44	RXA	Y00327	20030100067	Atrauman 7.5cm x 10cm Ktd Polyester Dres	1	7.00	6.50	20	2(
544	Q44	RXA	Y00327	20030100068	Atrauman 10cm x 20cm Ktd Polyester Dress	1	16.00	14.85	20	2(
545	Q44	RXA	Y00327	20030100109	Mesorb 20cm x 25cm Pfa Cellulose Dress	1	22.70	21.06	10	2(

In [13]:
```
#some top-level counts
print("No of unique practices in presentation level prescriptions data: ",
 len(practice_rxs.drop_duplicates(['PRACTICE'])))
print("No of unique practices in practice details data: ", len(practice_de
tails.drop_duplicates(['PRACTICE'])))
print("No of unique practices in pats per practice data: ", len(pats_per_p
ractice.drop_duplicates(['PRACTICE'])))
```

```
No of unique practices in presentation level prescriptions data:  9578
No of unique practices in practice details data:  9578
No of unique practices in pats per practice data:  7241
```

Description of data:

The data cover practices in England only. Scotland, Wales and Northern Ireland are excluded.

Prescriptions data
For each practice, there is a summary record (presentation level) for each BNF (British National Formulary) code detailing BNF name, total items prescribed, actual cost and quantity for that code (amongst other data) for April 2018. There are therefore multiple records for each practice, one for each BNF code that the practice has prescribed. No missing data was present in this dataset. There are 9578 practices with data in this dataset.

Practice data
For each practice, there is one record detailing Practice Code, Practice Name and Address details. There is therefore one record per practice in this dataset. No missing data was found in this dataset.

Prescription details data
This is a lookup file that tries to link the BNF code (9 digit for drugs and 4 digits for appliances) to a substance description. It is meant to be used in conjunction with the prescriptions data file, such that the first 9 characters (or 4 characters for appliances) of the BNF code in that file match with the code in this file (see https://digital.nhs.uk/data-and-information/areas-of-interest/prescribing/practice-level-prescribing-in-england-a-summary/practice-level-prescribing-data-more-information). However, since the NAME information provided in this file is contained in the BNFNAME field in the prescription data file (and in fact with a greater level of granularity since apart from the name, drug form information is also provided), it was decided not to use this data.

Practice details data
For some practices, this file contains one record per practice detailing (amongst other data) the number of patients registered for the practice. Of the 9578 practices with prescription data, only 7241 have details on number of patients.

1. London Practices data

In order to identify practices in Greater London, a list of Greater London postcodes was imported from https://www.doogal.co.uk/london_postcodes.php. This is a website maintained by a specialist who specialises in geo-mapping information. Note this list has NOT been validated and would need to be in a production environment. An alternative to this approach would have been to create some form of regular expression to express Greater London postcodes. However this would require some knowledge of the distinguishing features of London postcodes and it was felt that this "reference lookup" approach would be more accurate.

In [14]:
```
pc_url="https://www.doogal.co.uk/UKPostcodesCSV.ashx?area=London"
london_pc = pd.read_csv(pc_url)
print(london_pc.shape)
london_pc.head(1)
```

```
(319385, 43)
```

Out[14]:

	Postcode	In Use?	Latitude	Longitude	Easting	Northing	Grid Ref	County	District	W
0	BR1 1AA	Yes	51.401546	0.015415	540291	168873	TQ402688	Greater London	Bromley	Bro Tov

1 rows × 43 columns

In [15]:
```
#clean list of London postcodes

#remove any whitespace in the postcode for later comparison
london_pc['Postcode'] = london_pc['Postcode'].str.replace(' ', '')
#create list of London postcodes with whitepace removed
london_pc = london_pc.iloc[:, 0].tolist()
#check format of postcodes is correct
print(london_pc[0])

#Get London practices only

#remove any whitespace in the postcode for comparison with list created ab
ove
practice_details['POSTCODE2'] = practice_details['POSTCODE'].str.replace('
 ', '')
#compare with list to get all London practices
london_practices = practice_details[practice_details['POSTCODE2'].isin(lon
don_pc)]
print("Number of Greater London practices: ", len(london_practices))
london_practices['POSTCODE'].unique()
```

```
BR11AA
Number of Greater London practices:  1623
```

Out[15]:
```
array(['N20 0DH ', 'N3 2JP  ', 'NW2 1HS ', ..., 'IG1 2DR ', 'RM11 3SD',
       'RM10 7UP'], dtype=object)
```

In [16]:
```
#Get number of patients registered at London practices. We found above tha
t not all practices have patient numbers data

#merge London practices dataframe with pats_per_practice dataframe to get
number of pats data for London
london_practices_with_pat = pd.merge(london_practices, pats_per_practice,
how='inner', on='PRACTICE')
```

```
london_practices_with_pat.head()
print("Number of Greater London practices with patient number data: ", len
(london_practices_with_pat))
print("Number of Greater London practices without patient number data: ",
len(london_practices) - len(london_practices_with_pat))
print("Total patients for Greater London practices who have patient number
 data: ", np.sum(london_practices_with_pat['NUMBER_OF_PATIENTS']))
```

```
Number of Greater London practices with patient number data:  1300
Number of Greater London practices without patient number data:  323
Total patients for Greater London practices who have patient number data:
 9851021
```

In [17]:

```
#Get total number of prescriptions (rxs) and cost for Greater London pract
ices

#merge London practices dataframe with practice_rxs dataframe to get rxs d
ata for London practices - 1 to many
london_practices_rxs = pd.merge(london_practices, practice_rxs, how='inner
', on='PRACTICE')

#check all Greater London practices have rxs data
print("Greater London GP practices with rxs data:", len(london_practices_r
xs.drop_duplicates(['PRACTICE'])))

#get number and cost of rxs

## From https://digital.nhs.uk/data-and-information/areas-of-interest/pres
cribing/practice-level-prescribing-in-england-a-summary/practice-level-pre
scribing-glossary-of-terms
## "[ITEMS] gives the number of items for this presentation that were disp
ensed 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 thre
e prescription items."
print("Greater London GP practices total number of prescriptions:", np.sum
(london_practices_rxs["ITEMS"]))

print("Greater London GP practices total cost of prescriptions:", round(np
.sum(london_practices_rxs["ACTCOST"]),2))

##NOTE - The total cost figure of 77,881,446 was checked against
## https://files.digital.nhs.uk/publicationimport/pub02xxx/pub02274/pres-c
ost-anal-eng-2010-rep.pdf
## to ensure it was in the rough ballpark.
```

```
Greater London GP practices with rxs data: 1623
Greater London GP practices total number of prescriptions: 10564103
Greater London GP practices total cost of prescriptions: 77881446.74
```

In [18]:

```
#Get top 10 most frequent drug prescriptions

#standardise drug names by getting rid of any leading or trailing whitespa
ce
london_practices_rxs['BNFNAME2'] = london_practices_rxs['BNFNAME'].str.str
ip()
```

```
#sum quantity by BNFNAME2
grouped_drug = london_practices_rxs.groupby('BNFNAME2')['ITEMS'].sum()
drugs_quantity_london=pd.DataFrame(grouped_drug).reset_index()

#order by descending items
drugs_quantity_london.sort_values('ITEMS', ascending=False, inplace=True)

#top 10
drugs_quantity_london.head(10)
```

Out[18]:

	BNFNAME2	ITEMS
9335	Omeprazole_Cap E/C 20mg	240707
8300	Metformin HCl_Tab 500mg	208518
725	Amlodipine_Tab 5mg	198717
1020	Atorvastatin_Tab 20mg	183117
992	Aspirin Disper_Tab 75mg	168921
724	Amlodipine_Tab 10mg	155827
1022	Atorvastatin_Tab 40mg	152247
7284	Lansoprazole_Cap 30mg (E/C Gran)	150320
11114	Salbutamol_Inha 100mcg (200 D) CFF	142746
9753	Paracet_Tab 500mg	124082

In [19]:

```
#Get bottom 10 most frequent drug prescriptions
onlyone = drugs_quantity_london[drugs_quantity_london['ITEMS'] == 1]
print(onlyone.shape)

drugs_quantity_london.tail(10)
```

```
(2155, 2)
```

Out[19]:

	BNFNAME2	ITEMS
7440	Limb Seal-Tight PICC Mid-Arm Cover Lge W	1
7449	Lint Absorbent 100g	1
4265	Eakin Wound Pch Bung Closure Med 110mm x	1
12221	TYR Express 20_Pdr Sach 34g	1
12222	TYR gel_Pdr Sach 24g	1
4270	Easifast 10.75cm x 1m (Yellow) Stkntte E	1
7454	Liothyronine Sod_Cap 10mcg	1
4267	Eakin Wound Pch Fold & Tuck Closure Lge	1
4266	Eakin Wound Pch Bung Closure Sml Plus 86	1

13838	varicase Class 2 Thigh Open Toe Slc Band	1

2. Cambridge Practices data

Similarly to the London postcodes, in order to identify practices in the City of Cambridge (as opposed to Cambridgeshire), a list of City of Cambridge postcodes was imported from https://www.doogal.co.uk/AdministrativeAreas.php?district=E07000008. The list of wards in this list was validated by checking against the ward list provided by the Cambridge City Council: https://www.cambridge.gov.uk/ward-map and https://en.wikipedia.org/wiki/Cambridge.

In [20]:
```
pc_url="https://www.doogal.co.uk/AdministrativeAreasCSV.ashx?district=E07000008"
camb_pc = pd.read_csv(pc_url)
print(camb_pc.shape)
camb_pc.head(1)
```

(5852, 15)

Out[20]:

	Postcode	In Use?	Latitude	Longitude	Easting	Northing	Grid Ref	Ward	Parish
0	CB1 0AA	No	52.192267	0.137208	546184	257045	TL461570	Coleridge	Cambridge, unparished area

In [21]:
```
#clean Cambridge postcodes

#remove any whitespace in the postcode for later comparison
camb_pc['Postcode'] = camb_pc['Postcode'].str.replace(' ', '')
#create list of London postcodes with whitepace removed
camb_pc = camb_pc.iloc[:, 0].tolist()
#check format of postcodes is correct
print(camb_pc[0])

#Get Cambridge practices only

#compare with list above to get all Cambridge practices - use POSTCODE2 created above
cambridge_practices = practice_details[practice_details['POSTCODE2'].isin(camb_pc)]
print("Number of Cambridge practices: ", len(cambridge_practices))
```

```
CB10AA
Number of Cambridge practices:  21
```

In [22]:

```
#Get number of patients registered at Cambridge practices. We found above
that not all practices have patient numbers data

#check for duplicate practices in cambridge_practices dataset
print("Raw data number - cambridge_practices: ", len(cambridge_practices))
cambridge_practices_deduped = cambridge_practices.drop_duplicates(['PRACTI
CE'])
print("Raw data number - cambridge_practices deduped: ", len(cambridge_pra
ctices_deduped))

#merge cambridge practices dataframe with pats_per_practice dataframe to g
et number of pats data for cambridge
cambridge_practices_with_pat = pd.merge(cambridge_practices, pats_per_prac
tice, how='inner', on='PRACTICE')
cambridge_practices_with_pat.head()
print("Number of Cambridge practices with patient number data: ", len(camb
ridge_practices_with_pat))
print("Number of Cambridge practices without patient number data: ", len(c
ambridge_practices) - len(cambridge_practices_with_pat))
print("Total patients for Cambridge practices who have patient number data
: ", np.sum(cambridge_practices_with_pat['NUMBER_OF_PATIENTS']))
```

```
Raw data number - cambridge_practices:  21
Raw data number - cambridge_practices deduped:  21
Number of Cambridge practices with patient number data:  17
Number of Cambridge practices without patient number data:  4
Total patients for Cambridge practices who have patient number data:  1919
31
```

In [23]:

```
#Get total number of prescriptions (rxs) and cost for Cambridge practices

#merge cambridge practices dataframe with practice_rxs dataframe to get rx
s data for cambridge practices - 1 to many
cambridge_practices_rxs = pd.merge(cambridge_practices, practice_rxs, how=
'inner', on='PRACTICE')

#check all cambridge practices have rxs data
print("Cambridge practices with rxs data:", len(cambridge_practices_rxs.dr
op_duplicates(['PRACTICE'])))

#get number and cost of rxs
print("Cambridge GP practices total number of prescriptions:", np.sum(camb
ridge_practices_rxs["ITEMS"]))
print("Cambridge GP practices total cost of prescriptions:", round(np.sum(
cambridge_practices_rxs["ACTCOST"]),2))
```

```
Cambridge practices with rxs data: 21
Cambridge GP practices total number of prescriptions: 161368
Cambridge GP practices total cost of prescriptions: 1232480.72
```

In [24]:

```
#Get top 10 most frequent drug prescriptions

#standardise drug names by getting rid of any leading or trailing whitespa
ce
```

```
cambridge_practices_rxs['BNFNAME2'] = cambridge_practices_rxs['BNFNAME'].s
tr.strip()

#sum quantity by BNFNAME2
grouped_drug = cambridge_practices_rxs.groupby('BNFNAME2').ITEMS.sum()
drugs_quantity_cambridge=pd.DataFrame(grouped_drug).reset_index()

#order by descending
drugs_quantity_cambridge.sort_values('ITEMS', ascending=False, inplace=Tru
e)

#top 10
drugs_quantity_cambridge.head(10)
```

Out[24]:

	BNFNAME2	ITEMS
2973	Omeprazole_Cap E/C 20mg	5076
296	Atorvastatin_Tab 20mg	3158
278	Aspirin Disper_Tab 75mg	2479
208	Amlodipine_Tab 5mg	2269
3563	Salbutamol_Inha 100mcg (200 D) CFF	2163
3103	Paracet_Tab 500mg	2094
2549	Metformin HCl_Tab 500mg	1907
1665	Folic Acid_Tab 5mg	1818
202	Amitriptyline HCl_Tab 10mg	1709
2278	Levothyrox Sod_Tab 25mcg	1659

In [25]:

```
#Get bottom 10 most frequent drug prescriptions
onlyone = drugs_quantity_cambridge[drugs_quantity_cambridge['ITEMS'] == 1]
print(onlyone.shape)
drugs_quantity_cambridge.tail(10)
```

```
(1211, 2)
```

Out[25]:

	BNFNAME2	ITEMS
2324	Lisdexamfetamine_Cap 70mg	1
2319	LiquiBand Flow Control 0.5g Amp Skin Adh	1
2316	Liq Paraf_Bath Add 65%	1
2312	Liq Paraf Light_Bath Oil 90%	1
2309	Lipitor_Tab 80mg	1
2307	Lipitor_Tab 20mg	1
2306	Lipitor_Tab 10mg	1
2305	Lipantil Micro 200_Cap 200mg	1

2304	Liothyronine Sod_Tab 5mcg	1
2142	Jade_Male Urin Day & Night Use + Pressur	1

In [26]:
```
#create a dataframe with summary statistics for both London and Cambridge
- for practices with patient information only

#keep those subsets of data where practices have patient numbers
london_practices_rxs_pats = pd.merge(london_practices_with_pat, london_pra
ctices_rxs, how='inner', on='PRACTICE')
london_practices_rxs_pats_sc = london_practices_rxs_pats.drop_duplicates([
'PRACTICE'])
#print("Check - should be 1300",len(london_practices_rxs_pats_sc))
cambridge_practices_rxs_pats = pd.merge(cambridge_practices_with_pat, camb
ridge_practices_rxs, how='inner', on='PRACTICE')
cambridge_practices_rxs_pats_sc = cambridge_practices_rxs_pats.drop_duplic
ates(['PRACTICE'])
#print("Check - should be 50",len(cambridge_practices_rxs_pats_sc))

london_practices_with_patinfo = len(london_practices_rxs_pats.drop_duplica
tes(['PRACTICE']))
cambridge_practices_with_patinfo = len(cambridge_practices_rxs_pats.drop_d
uplicates(['PRACTICE']))

london_total_pats = np.sum(london_practices_rxs_pats_sc["NUMBER_OF_PATIENT
S"])
cambridge_total_pats = np.sum(cambridge_practices_rxs_pats_sc["NUMBER_OF_P
ATIENTS"])

london_total_costs = round(np.sum(london_practices_rxs_pats["ACTCOST"]),2)
cambridge_total_costs = round(np.sum(cambridge_practices_rxs_pats["ACTCOST
"]),2)

london_total_rxs = np.sum(london_practices_rxs_pats["ITEMS"])
cambridge_total_rxs = np.sum(cambridge_practices_rxs_pats["ITEMS"])

summ_df = pd.DataFrame({ 'Area' : ['London', 'Cambridge'],
                         'Practices' : [london_practices_with_patinfo, cam
bridge_practices_with_patinfo],
                         'Total patients' : [london_total_pats, cambridge_
total_pats],
                         'Total items' : [london_total_rxs, cambridge_tota
l_rxs],
                         'Total cost' : [london_total_costs, cambridge_tot
al_costs]
                        })

summ_df['Cost per rx'] = round(summ_df['Total cost']/summ_df['Total items'
],2)
summ_df['Spend per patient'] = round(summ_df['Total cost']/summ_df['Total
patients'],2)
summ_df['Spend per practice'] = round(summ_df['Total cost']/summ_df['Pract
ices'], 2)
summ_df['Cost per rx'] = round(summ_df['Total cost']/summ_df['Total items'
],2)
summ_df['Pats per practice'] = round(summ_df['Total patients']/summ_df['Pr
```

```
actices'])
summ_df['Rxs per patient'] = round(summ_df['Total items']/summ_df['Total p
atients'],2)
print(summ_df)
```

```
        Area  Practices   Total cost  Total items  Total patients  \
0  London     1300       76695586.17  10430264     9851021
1  Cambridge  17         1227048.96   160494       191931

   Cost per rx  Spend per patient  Spend per practice  Pats per practice
\
0  7.35         7.79               58996.60            7578.0

1  7.65         6.39               72179.35            11290.0


   Rxs per patient
0  1.06
1  0.84
```

Discussion - London versus Cambridge practice and prescribing patterns

Table 1 - Summary statistics for London and Cambridge, April 2018

Area	**Practices**	**Total cost (£)**	**Total items**	**Total patients**	**Cost per rx (£)**	**Spend per patient (£)**	**Spend per practice (£)**	**Pats per practice**
London	**1,300**	**76,695,586.17**	**10,430,264**	**9,851,021**	**7.0**	**7.79**	**58,996.60**	**7,578**
Cambridge	**17**	**1,227,048.96**	**160,494**	**191,931**	**8.0**	**6.39**	**72,179.35**	**11,290**

The table above summarises data for practices with data on patient numbers. Of the 1623 practices with Greater London postcodes, 1300 have data on number of patients. Of the 21 practices with City of Cambridge postcodes, 17 have data on number of patients.
City of Cambridge practices are larger, having on average 11,290 patients compared with the London average of 7,578 patients per practice. This leads to larger average total spend on prescriptions for Cambridge practices, £72,179 compared with £58,997 for London practices.
The average cost of prescriptions per patient is lower in Cambridge compared to London (£6.39 vs. £7.79), although the average cost per prescription (£8) is higher than London (£7), probably reflecting the fact that Cambridge patients have fewer prescriptions written on average, compared with London (0.84 vs 1.06).

Table 2 - Summary of London Practices data, April 2018

Number of Greater London practices	1,623

Number of Greater London practices with patient number data	1,300
Number of Greater London practices without patient number data	323
Total patients for Greater London practices who have patient number data	9,851,021
Total number of prescriptions for Greater London practices	10,564,103
Total cost of prescriptions for Greater London practices	$ £ $77,881,446.74
Top 10 most frequent prescriptions	**Number prescribed**
Omeprazole_Cap E/C 20mg	240,707
Metformin HCl_Tab 500mg	208,518
Amlodipine_Tab 5mg	198,717
Atorvastatin_Tab 20mg	183,117
Aspirin Disper_Tab 75mg	168,921
Amlodipine_Tab 10mg	155,827
Atorvastatin_Tab 40mg	152,247
Lansoprazole_Cap 30mg (E/C Gran)	150,320
Salbutamol_Inha 100mcg (200 D) CFF	142,746
Paracet_Tab 500mg	124,082
Examples of some least frequent prescriptions	**Number prescribed**
Limb Seal-Tight PICC Mid-Arm Cover Lge W	1
Lint Absorbent 100g	1
Eakin Wound Pch Bung Closure Med 110mm x	1
TYR Express 20_Pdr Sach 34g	1
TYR gel_Pdr Sach 24g	1
Easifast 10.75cm x 1m (Yellow) Stkntte E	1
Liothyronine Sod_Cap 10mcg	1
Eakin Wound Pch Fold & Tuck Closure Lge	1
Eakin Wound Pch Bung Closure Sml Plus 86	1
varicase Class 2 Thigh Open Toe Slc Band	1

Table 3 - Summary of Cambridge Practices data, April 2018

Number of Cambridge practices	21
Number of Cambridge practices with patient number data	17
Number of Cambridge practices without patient number data	4
Total patients for Cambridge practices who have patient number data	191,931
Total number of prescriptions for Cambridge practices	161,368
Total cost of prescriptions for Cambridge practices	$ £ $1,232,480.72
Top 10 most frequent prescriptions	**Number prescribed**
Omeprazole_Cap E/C 20mg	5,076
Atorvastatin_Tab 20mg	3,158
Aspirin Disper_Tab 75mg	2,479
Amlodipine_Tab 5mg	2,269
Salbutamol_Inha 100mcg (200 D) CFF	2,163
Paracet_Tab 500mg	2,094
Metformin HCl_Tab 500mg	1,907
Folic Acid_Tab 5mg	1,818
Amitriptyline HCl_Tab 10mg	1,709
Levothyrox Sod_Tab 25mcg	1,659
Examples of some least frequent prescriptions	**Number prescribed**
Lisdexamfetamine_Cap 70mg	1
LiquiBand Flow Control 0.5g Amp Skin Adh	1
Liq Paraf_Bath Add 65%	1
Liq Paraf Light_Bath Oil 90%	1
Lipitor_Tab 80mg	1
Lipitor_Tab 20mg	1
Lipitor_Tab 10mg	1
Lipantil Micro 200_Cap 200mg	1
Liothyronine Sod_Tab 5mcg	1
Jade_Male Urin Day & Night Use + Pressur	1

Looking at the top 10 drugs prescribed (see Tables 2 and 3 above), there is substantial overlap in the top 10 prescriptions for both regions with Omeprazole 20mg capsule in top place for both. Metformin, Atovarstatin, Aspirin, Amlodipone, Salbutamol and Paracetemol, in various forms, all appear in the top 10 for both London and Cambridge. However, London has Lansoprazole 30mg capsule in its top 10, unlike Cambridge, while Cambridge has Folic Acid, Amitriptyline and Levothyrox in its top 10, unlike London. Looking at the least prescribed drugs is not as informative as there seems to be a long tail of single prescriptions: 2155 for London and 1211 for Cambridge. Examples of some of these single prescriptions are given in Tables 2 and 3.

For all practices in London in April (including ones with no information on number of patients), a total of 10,564,103 prescriptions were dispensed with a total cost of £77,881,447. The corresponding figure for Cambridge was 161,368 items with a total cost of £1,232,480.72.

3. Cardiovascular and Antidepressant prescriptions, April 2018

From https://ebmdatalab.net/prescribing-data-bnf-codes/ it has been worked out that:
1. Cardiovascular drugs have a BNFcode starting with '02'.
2. Antidepressant drugs have a BNFcode starting with '0403'.

In [27]:
```
#get all cardio-vascular rxs - these have BNF code starting with "02"
cv_rxs = practice_rxs[practice_rxs['BNFCODE'].str[0:2] == "02"]
#get all anti-depressant rxs - these have BNF code starting with "0403"
ad_rxs = practice_rxs[practice_rxs['BNFCODE'].str[0:4] == "0403"]
print(cv_rxs.head())
print(ad_rxs.head())

#get total no of rxs and cost for cardiovascular rxs
print("Cardiovascular total number of prescriptions:", np.sum(cv_rxs["ITEM
S"]))
print("Cardiovascular total cost of prescriptions:", round(np.sum(cv_rxs["
ACTCOST"]),2))

#get total no of rxs and cost for cardiovascular rxs
print("Antidepressant total number of prescriptions:", np.sum(ad_rxs["ITEM
S"]))
print("Antidepressant total cost of prescriptions:", round(np.sum(ad_rxs["
ACTCOST"]),2))
```

```
     SHA  PCT  PRACTICE          BNFCODE  \
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

                                     BNFNAME  ITEMS   NIC  ACTCOST  QUANT
ITY  \
28   Propranolol HCl_Tab 10mg                 4      7.12  6.65     224
```

```
29   Propranolol HCl_Tab 40mg                   3      1.35  1.59     42

337  Bumetanide_Tab 1mg                         1      0.26  0.35     6

338  Furosemide_Tab 20mg                        1      0.13  0.23     10

339  Furosemide_Tab 40mg                        1      0.17  0.27     14


     PERIOD    CHEMSUB
28   201804  0204000R0
29   201804  0204000R0
337  201804  0202020D0
338  201804  0202020L0
339  201804  0202020L0
    SHA  PCT PRACTICE         BNFCODE  \
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

                                   BNFNAME  ITEMS    NIC  ACTCOST  QUANT
ITY  \
9   Trazodone HCl_Cap 50mg                 1      1.19   1.22     14

10  Citalopram Hydrob_Tab 20mg             1      1.17   1.20     14

11  Citalopram Hydrob_Tab 10mg             1      0.76   0.82     14

12  Paroxetine HCl_Oral Soln 10mg/5ml S/F  1      15.99  14.94    263

13  Paroxetine HCl_Tab 10mg                1      16.50  15.41    49


    PERIOD    CHEMSUB
9   201804  0403010X0
10  201804  0403030D0
11  201804  0403030D0
12  201804  0403030P0
13  201804  0403030P0
Cardiovascular total number of prescriptions: 26449832
Cardiovascular total cost of prescriptions: 90193834.02
Antidepressant total number of prescriptions: 5715873
Antidepressant total cost of prescriptions: 16853470.86
```

Table 4 - Summary of Cardiovascular and Antidepressant prescriptions, April 2018

Number of Cardiovascular prescriptions across all practices	26,449,832
Cost of Cardiovascular prescriptions across all practices	$ £ $90,193,834.02

Number of Antidepressant prescriptions across all practices	5,715,873
Cost of Cardiovascular prescriptions across all practices	$ £ $16,853,470.86

Discussion - Cardiovascular and Antidepressant prescription across all practices, April 2019

As can be seen from Table 4 above, across England, the number and cost of cardiovascular prescriptions is much larger than the corresponding figures for anti-depressants. At £90,193,834 vs. £16,853,471, the actual cost of cardiovascular prescriptions is about 5 times as much as for anti-depressants. This roughly corresponds to the amount of prescriptions, suggesting the cost per prescription for the two therapy areas is roughly similar (cardiovascular prescriptions are slightly more expensive on average). It may be worth watching for trends in prescribing for these two therapy areas. If for example, the diagnosis or prevalence of depression is rising, the costs for antidepressants are likely to rise too. As the proportion of the population that is older rises, the costs of cardiovascular prescriptions may also rise.

4. Total costs and relative spending per patient, April 2018

In [28]:

```
#get practices which have number of patients data
pracs_with_pat_info = pd.merge(practice_details, pats_per_practice, how='i
nner', on='PRACTICE')
print("Practices with patient data", len(pracs_with_pat_info))

#for these practice get their rxs data
pracs_with_pat_info_rxs = pd.merge(pracs_with_pat_info, practice_rxs, how=
'inner', on='PRACTICE')

#get the total cost for each practice
pracs_total_cost = pracs_with_pat_info_rxs.groupby('PRACTICE')['ACTCOST'].
sum().reset_index()
print(pracs_total_cost.shape)

#merge back
practice_level = pd.merge(pracs_with_pat_info, pracs_total_cost, how='inne
r', on='PRACTICE')
print(practice_level.shape)
practice_level['AVERAGE_COST'] = round(practice_level['ACTCOST']/practice_
level['NUMBER_OF_PATIENTS'],2)
practice_level.head(5)
```

```
Practices with patient data 7191
(7191, 2)
(7191, 19)
```

Out[28]:

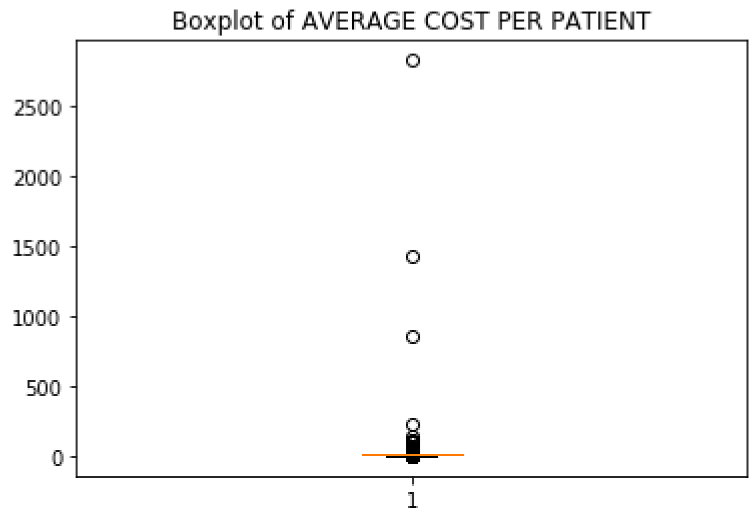
	DATE	PRACTICE	PRACTICE_NAME	ADD1	ADD2	ADD3	
0	201804	A81001	THE DENSHAM SURGERY	THE HEALTH CENTRE	LAWSON STREET	STOCKTON-ON-TEES	CLE

1	201804	A81002	QUEENS PARK MEDICAL CENTRE	QUEENS PARK MEDICAL CTR	FARRER STREET	STOCKTON ON TEES	CLE
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	CLE

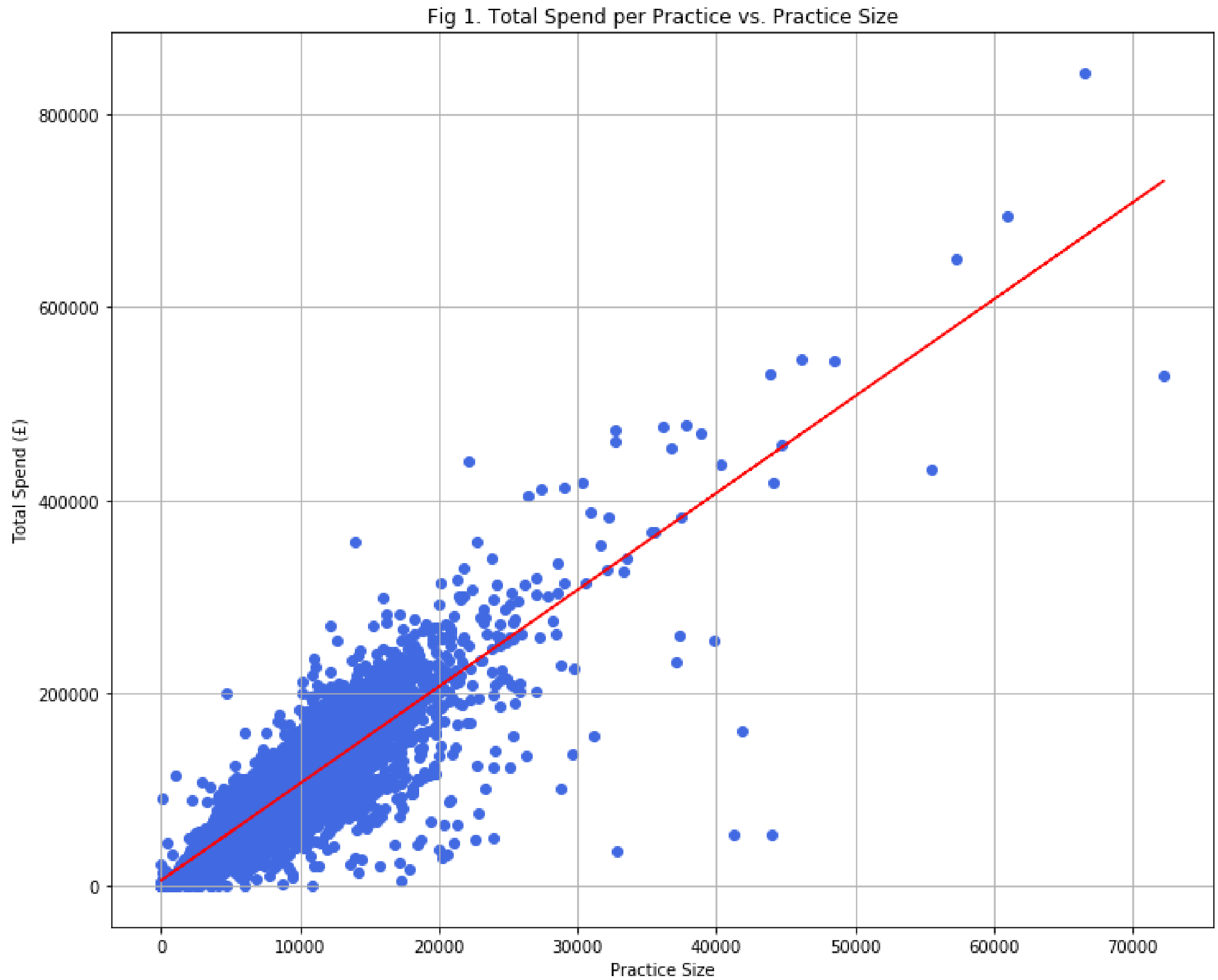
In [29]:

```
#do some checking before plotting

print(practice_level['NUMBER_OF_PATIENTS'].describe())
print(practice_level['AVERAGE_COST'].describe())

#Check the relative spend data - shows some extreme outliers
fig = plt.figure()
ax1 = fig.add_subplot(111)
ax1.boxplot(practice_level['AVERAGE_COST'])
ax1.set_title("Boxplot of AVERAGE COST PER PATIENT")
plt.show()
```

```
count     7191.000000
mean      8207.557224
std       5161.846053
min          3.000000
25%       4557.000000
50%       7278.000000
75%      10742.500000
max      72227.000000
Name: NUMBER_OF_PATIENTS, dtype: float64
count    7191.000000
mean       11.606484
std        38.868980
min         0.000000
25%         8.875000
50%        10.910000
75%        12.690000
max      2830.020000
Name: AVERAGE_COST, dtype: float64
```



In [30]:
```
#Create scatter plot for total spend
x = practice_level['NUMBER_OF_PATIENTS']
y = practice_level['ACTCOST']

#create scatter plot and trend line for total spend
fig = plt.figure(figsize=(12,10))
ax = fig.add_subplot(111)
ax.scatter(x, y, color='royalblue')
ax.grid(b=True)

z = np.polyfit(x, y, 1)
p = np.poly1d(z)
plt.plot(x,p(x),"r--")

ax.set_title("Fig 1. Total Spend per Practice vs. Practice Size")
ax.set_ylabel("Total Spend (£)")
ax.set_xlabel("Practice Size")
plt.show()
```

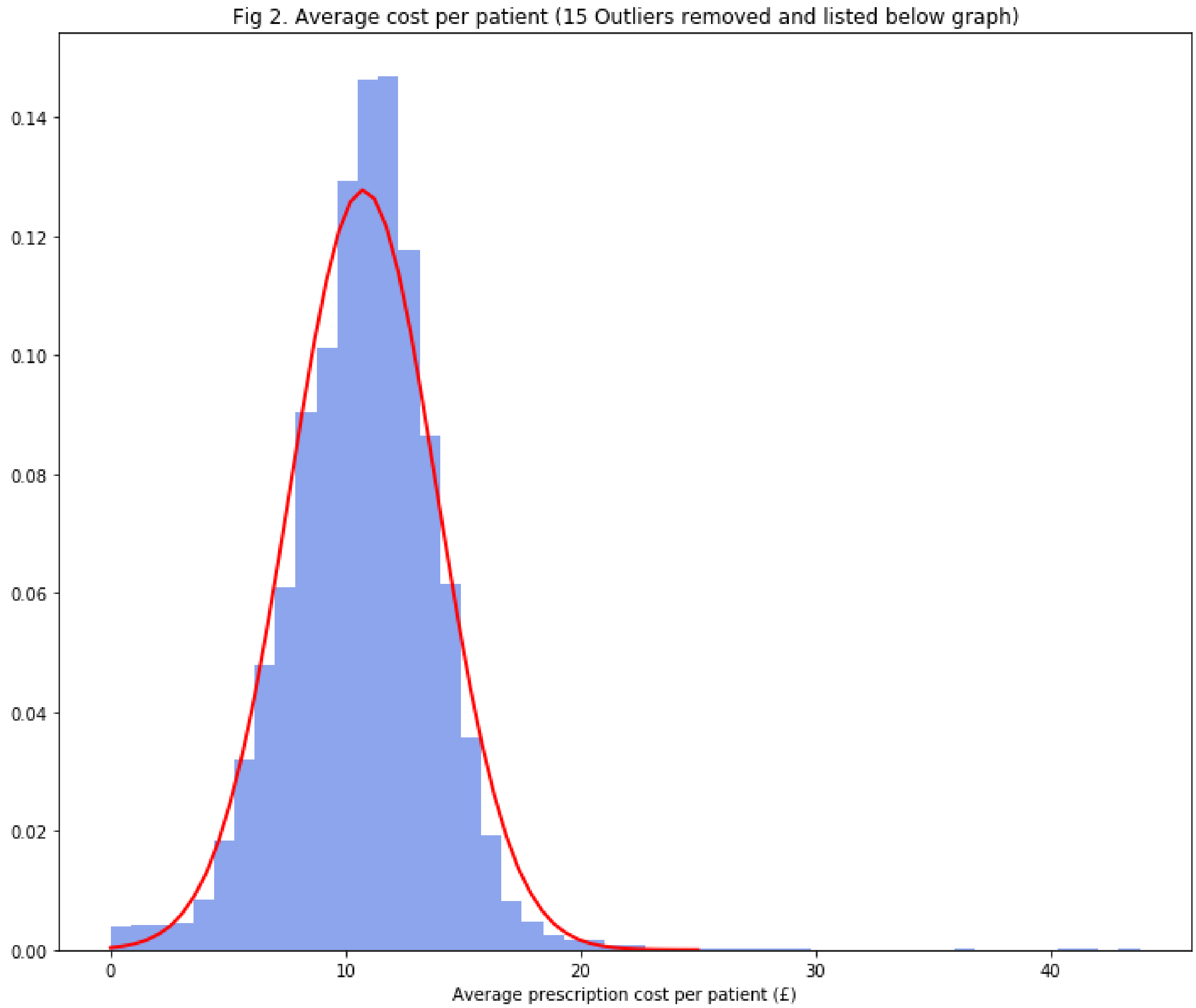


In [31]:

```
#Create histogram for Relative Spend
#Boxplot above shows some extreme outliers, these are removed first
practice_level_low = practice_level[practice_level['AVERAGE_COST'] <= 50]
print(practice_level_low.shape)
practice_level_high = practice_level[practice_level['AVERAGE_COST'] > 50]
practice_level_high = practice_level_high[['PRACTICE_NAME','POSTCODE_x', '
ACTCOST', 'AVERAGE_COST']]
print(practice_level_high.shape)

x=practice_level_low['AVERAGE_COST']
mu, std = norm.fit(x)

fig = plt.figure(figsize=(12,10), )
ax = fig.add_subplot(111)
ax.hist(x, color='royalblue', bins=50, density=True, alpha=0.6)

x = np.linspace(0,25)
p = norm.pdf(x, mu, std)
ax.plot(x, p, 'k', linewidth=2, color='r')
ax.set_xlabel("Average prescription cost per patient (£)")
ax.set_title("Fig 2. Average cost per patient (15 Outliers removed and lis
ted below graph)")
plt.show()
```

```
print('\033[1m' + 'All 15 Practices with excessive levels of average spend
 per patient (>£50)' + '\033[0m')
noind = practice_level_high.reset_index(drop=True)
noind.head(20)
```

```
(7176, 20)
(15, 4)
```



All 15 Practices with excessive levels of average spend per patient (>£50)

Out[31]:

	PRACTICE_NAME	POSTCODE_x	ACTCOST	AVERAGE_COST
0	ROYAL HOSPITAL CHELSEA	SW3 4SR	14850.18	50.34
1	KEYHEALTH MEDICAL CENTRE	EN9 1NP	3099.81	221.42
2	NIGHTINGALE HOUSE	SW12 8NB	17924.38	97.95
3	DR GOULD AND AL-TIMMAN	LS7 3QB	892.19	68.63
4	H&R P C SPECIAL SCHEME	TN34 1BA	1037.85	103.78
5	THE HOMELESS HEALTHCARE TEAM	GL1 3NF	4626.12	57.83
6	SUSSEX DOWN AND WEALD SPECIAL SCHEME	BN22 8DR	755.39	50.36

7	SAWBRIDGEWORTH MEDICAL SERVICES	CM21 0HH	90691.01	855.58
8	VERNOVA HEALTHCARE CIC	SK11 6JL	22640.16	2830.02
9	LCD WAKEFIELD WIC	WF1 2SN	7793.03	63.88
10	CARE HOMES MEDICAL PRACTICE	M5 4DG	114890.10	111.22
11	CALDERDALE SAFE HAVEN SERVICE	HD1 9RX	835.28	139.21
12	COMPASS HEALTH	BS2 8JP	4295.03	1431.68
13	HEALTH 1000 LTD	IG3 8YB	44507.19	100.47
14	BOWTHORPE CARE VILLAGE - NPL	NR5 9BF	14626.01	110.80

Discussion - Total Costs and Relative costs for patients for all practices, April 2019

As may be expected, there seems to be a strong linear trend between total spending per practice and number of patients registered to the practice (Fig 1. above). The vast majority of practices have less than 30,000 patients registered and are under the £400,000 limit for total spend on prescriptions. However in spite of this trend, there seem to be some large variations in total spend between practices of similar size. While it may be tempting to try and compare practices of similar size with a large difference in spending, it should be noted that practices differ significantly in many ways, not just number of patients registered. For example the age profile and soci-economic status of the sub-populations that practices serve may be completely different. This would lead to different disease and treatment profiles for different practices. This is a limitation of the data provided as we cannot drill down to find data on factors like age profile and socio-economic status for practices. If more information is required, it may be possible to link to, for example, data on socio-economic status using the practice postcode. This may help in comparing practices. However all such drilling down into the data should be cognizant of the various issues with patient confidentiality and data ethics.

Fig 2. above shows average cost per patient once 15 outliers have been removed (these are listed below Fig. 2). The distribution of cost once outliers have been removed is largely normal. In this case, somewhat arbitrarily an outlier is considered to be any average spend per patient over £50. This seems reasonable since the average prescribing cost per patient (for April 2018) is about the £11 mark judging from Fig. 2. Looking at the outliers, some practices have very large average costs per patient, it would definitely be worth examining the data for these practices in more detail to see if there is any reason for the large average spend.

Assignment B

Overview

WHO Mortality data were downloaded from https://www.who.int/healthinfo/mortality_data/en/. The data records the cause of death (by ICD code) for various countries for various years. In addition to the mortality data there are two files that enable lookup of country names and country population for various years. Total deaths in 2010 were reported for Iceland, Italy and New Zealand. Distribution of death for all years was reported for Italy as were the top 5 causes of death from neoplasm. Neoplasm deaths for Australia in 2010 were reported and compared with Italy.

0. Data checking and Cleaning

In [32]:
```
#Read in raw data files for WHO mortality data

#ICD mortality data part 1
url = 'https://www.who.int/healthinfo/statistics/Morticd10_part1.zip?ua=1'
mortality1 = pd.read_csv(url, encoding = "ISO-8859-1", compression='zip',
low_memory=False)
#ICD mortality data part 2
url = 'https://www.who.int/healthinfo/statistics/Morticd10_part2.zip?ua=1'
mortality2 = pd.read_csv(url, encoding = "ISO-8859-1", compression='zip',
low_memory=False)
#Country information
url = 'https://www.who.int/healthinfo/statistics/country_codes.zip?ua=1'
country_codes = pd.read_csv(url, encoding = "ISO-8859-1", compression='zip
')
#Population information
url = 'https://www.who.int/healthinfo/Pop.zip?ua=1'
population = pd.read_csv(url, encoding = "ISO-8859-1", compression='zip')

#concatenate mortality data
print(mortality1.shape)
print(mortality2.shape)
mortality = pd.concat([mortality1, mortality2])
```

```
(1388106, 39)
(2316790, 39)
```

In [33]:
```
#check mortality data - uses examine function defined in Assignment A
examine(mortality)
mortality.head(5)
```

```
(3704896, 39)
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3704896 entries, 0 to 2316789
Data columns (total 39 columns):
Country       3704896 non-null int64
Admin1        84173 non-null float64
SubDiv        2707 non-null object
Year          3704896 non-null int64
List          3704896 non-null object
Cause         3704896 non-null object
Sex           3704896 non-null int64
Frmat         3704896 non-null int64
IM_Frmat      3704896 non-null int64
Deaths1       3704896 non-null int64
Deaths2       3702654 non-null float64
Deaths3       3702654 non-null float64
Deaths4       3537648 non-null float64
Deaths5       3537648 non-null float64
Deaths6       3537648 non-null float64
Deaths7       3702654 non-null float64
Deaths8       3699669 non-null float64
```

```
Deaths9       3702654 non-null float64
Deaths10      3699669 non-null float64
Deaths11      3702654 non-null float64
Deaths12      3699669 non-null float64
Deaths13      3702654 non-null float64
Deaths14      3699669 non-null float64
Deaths15      3702654 non-null float64
Deaths16      3699669 non-null float64
Deaths17      3702654 non-null float64
Deaths18      3699669 non-null float64
Deaths19      3702654 non-null float64
Deaths20      3699345 non-null float64
Deaths21      3702330 non-null float64
Deaths22      3691478 non-null float64
Deaths23      3691478 non-null float64
Deaths24      3220900 non-null float64
Deaths25      3220900 non-null float64
Deaths26      3702654 non-null float64
IM_Deaths1    3702653 non-null float64
IM_Deaths2    2863458 non-null float64
IM_Deaths3    2952678 non-null float64
IM_Deaths4    2952678 non-null float64
dtypes: float64(30), int64(6), object(3)
memory usage: 1.1+ GB
None
                count         mean          std    min     25%     50%  \
Country     3704896.0  3241.099142  1012.568206  1060.0  2240.0  3320.0
Admin1        84173.0   901.553610     0.497121   901.0   901.0   902.0
Year        3704896.0  2006.714577     5.630995  1988.0  2002.0  2007.0
Sex         3704896.0     1.511633     0.726999     1.0     1.0     1.0
Frmat       3704896.0     0.188641     0.582099     0.0     0.0     0.0
IM_Frmat    3704896.0     2.445921     2.809113     1.0     1.0     1.0
Deaths1     3704896.0   185.894292  6876.698655     0.0     1.0     3.0
Deaths2     3702654.0     3.882018   161.932250     0.0     0.0     0.0
Deaths3     3702654.0     0.524806    25.019029     0.0     0.0     0.0
Deaths4     3537648.0     0.207538     8.472934     0.0     0.0     0.0
Deaths5     3537648.0     0.143425     5.723831     0.0     0.0     0.0
Deaths6     3537648.0     0.116541     4.618529     0.0     0.0     0.0
Deaths7     3702654.0     0.485666    18.649950     0.0     0.0     0.0
Deaths8     3699669.0     0.526512    20.212583     0.0     0.0     0.0
Deaths9     3702654.0     1.400593    63.381939     0.0     0.0     0.0
Deaths10    3699669.0     2.179165   103.941378     0.0     0.0     0.0
Deaths11    3702654.0     2.629331   127.276727     0.0     0.0     0.0
Deaths12    3699669.0     3.083791   146.220989     0.0     0.0     0.0
Deaths13    3702654.0     3.679645   165.696808     0.0     0.0     0.0
Deaths14    3699669.0     4.794628   215.524123     0.0     0.0     0.0
Deaths15    3702654.0     6.489613   287.901608     0.0     0.0     0.0
Deaths16    3699669.0     8.529558   367.206484     0.0     0.0     0.0
Deaths17    3702654.0    10.303949   417.583356     0.0     0.0     0.0
Deaths18    3699669.0    12.741290   515.337567     0.0     0.0     0.0
Deaths19    3702654.0    15.523331   612.328752     0.0     0.0     0.0
Deaths20    3699345.0    19.731551   781.446428     0.0     0.0     0.0
Deaths21    3702330.0    23.371660   917.027837     0.0     0.0     0.0
Deaths22    3691478.0    24.744463   982.094635     0.0     0.0     0.0
Deaths23    3691478.0    24.117928  1023.807205     0.0     0.0     0.0
Deaths24    3220900.0    13.107108   633.199648     0.0     0.0     0.0
Deaths25    3220900.0     5.837956   326.735907     0.0     0.0     0.0
```

```
Deaths26     3702654.0  0.361918     29.037955    0.0      0.0      0.0
IM_Deaths1   3702653.0  2.412954     132.045719   0.0      0.0      0.0
IM_Deaths2   2863458.0  0.552906     25.912633    0.0      0.0      0.0
IM_Deaths3   2952678.0  0.370973     17.712193    0.0      0.0      0.0
IM_Deaths4   2952678.0  0.935033     50.682498    0.0      0.0      0.0

                75%        max
Country      4188.0   5150.0
Admin1       902.0    902.0
Year         2012.0   2017.0
Sex          2.0      9.0
Frmat        0.0      9.0
IM_Frmat     1.0      9.0
Deaths1      12.0     1400232.0
Deaths2      0.0      42097.0
Deaths3      0.0      8147.0
Deaths4      0.0      1802.0
Deaths5      0.0      1254.0
Deaths6      0.0      973.0
Deaths7      0.0      3556.0
Deaths8      0.0      4620.0
Deaths9      0.0      18192.0
Deaths10     0.0      27019.0
Deaths11     0.0      34991.0
Deaths12     0.0      41331.0
Deaths13     0.0      51922.0
Deaths14     0.0      84961.0
Deaths15     0.0      109955.0
Deaths16     1.0      130223.0
Deaths17     1.0      121231.0
Deaths18     1.0      166218.0
Deaths19     1.0      165157.0
Deaths20     1.0      169005.0
Deaths21     1.0      207596.0
Deaths22     1.0      209735.0
Deaths23     1.0      236249.0
Deaths24     0.0      201120.0
Deaths25     0.0      117257.0
Deaths26     0.0      14295.0
IM_Deaths1   0.0      42097.0
IM_Deaths2   0.0      9476.0
IM_Deaths3   0.0      5786.0
IM_Deaths4   0.0      17654.0
          count  unique   top      freq
SubDiv   2707      1       A30   2707
List     3704896   5       104   3344705
Cause    3704896   11396   AAA   4115
```

Out[33]:

	Country	Admin1	SubDiv	Year	List	Cause	Sex	Frmat	IM_Frmat	Deaths1	...	Deaths21
0	1400	NaN	NaN	2001	101	1000	1	7	8	332	...	95.0
1	1400	NaN	NaN	2001	101	1000	2	7	8	222	...	112.0
2	1400	NaN	NaN	2001	101	1001	1	7	8	24	...	5.0
3	1400	NaN	NaN	2001	101	1001	2	7	8	14	...	6.0

4	1400	NaN	NaN	2001	101	1002	1	7	8	0	...	0.0

5 rows × 39 columns

In [34]:
```
examine(country_codes)
```

```
(227, 2)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 227 entries, 0 to 226
Data columns (total 2 columns):
country    227 non-null int64
name       227 non-null object
dtypes: int64(1), object(1)
memory usage: 3.6+ KB
None
         count         mean          std     min     25%     50%     75%  \
country  227.0  2893.612335  1266.697507  1010.0  1565.0  3050.0  4095.0


            max
country  5207.0
     count unique                    top freq
name   227    227    Germany, West Berlin    1
```

Out[34]:

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

In [35]:
```
#tidy up country codes data

#capitalise name of country to make compatible with mortality data
country_codes.rename(columns = {'country':'Country'}, inplace=True)
country_codes.head(1)
```

Out[35]:

	Country	name
0	1010	Algeria

In [36]:
```
#check population data
examine(population)

#for each country, 2 population records for every year for male and female
```

```
(9383, 33)
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 9383 entries, 0 to 9382
Data columns (total 33 columns):
Country    9383 non-null int64
Admin1     82 non-null float64
SubDiv     138 non-null object
Year       9383 non-null int64
Sex        9383 non-null int64
Frmat      9383 non-null int64
Pop1       9383 non-null float64
Pop2       9247 non-null float64
Pop3       9247 non-null float64
Pop4       5178 non-null float64
Pop5       5178 non-null float64
Pop6       5178 non-null float64
Pop7       9247 non-null float64
Pop8       9229 non-null float64
Pop9       9247 non-null float64
Pop10      9229 non-null float64
Pop11      9247 non-null float64
Pop12      9229 non-null float64
Pop13      9247 non-null float64
Pop14      9229 non-null float64
Pop15      9247 non-null float64
Pop16      9229 non-null float64
Pop17      9247 non-null float64
Pop18      9229 non-null float64
Pop19      9247 non-null float64
Pop20      9185 non-null float64
Pop21      9091 non-null float64
Pop22      8227 non-null float64
Pop23      8227 non-null float64
Pop24      1168 non-null float64
Pop25      1168 non-null float64
Pop26      9229 non-null float64
Lb         9157 non-null float64
dtypes: float64(28), int64(4), object(1)
memory usage: 2.4+ MB
None
          count         mean          std     min        25%        50%
  \
Country  9383.0  3.512572e+03  9.529958e+02  1060.0  2450.00     4040.0

Admin1   82.0    9.012439e+02  4.320773e-01  901.0   901.00      901.0

Year     9383.0  1.983523e+03  1.797395e+01  1950.0  1969.00     1983.0

Sex      9383.0  1.503997e+00  5.290133e-01  1.0     1.00        2.0

Frmat    9383.0  1.669615e+00  1.438715e+00  0.0     1.00        1.0

Pop1     9383.0  9.980086e+06  1.832962e+07  0.0     1062100.00  3250600.0

Pop2     9247.0  1.693578e+05  3.088838e+05  0.0     21800.00    51047.0

Pop3     9247.0  4.388227e+05  1.097184e+06  0.0     29500.00    96200.0

Pop4     5178.0  1.412850e+05  2.208294e+05  0.0     26100.00    51298.0
```

Pop5	5178.0	1.419200e+05	2.225388e+05	0.0	26200.00	51635.5
Pop6	5178.0	1.423836e+05	2.240680e+05	0.0	26376.00	51849.0
Pop7	9247.0	8.336949e+05	1.503878e+06	0.0	111142.50	253574.0
Pop8	9229.0	8.204250e+05	1.478021e+06	0.0	107300.00	252979.0
Pop9	9247.0	8.082447e+05	1.463231e+06	0.0	97000.00	251300.0
Pop10	9229.0	7.913415e+05	1.450529e+06	0.0	87500.00	252040.0
Pop11	9247.0	7.704808e+05	1.434296e+06	0.0	80015.00	249400.0
Pop12	9229.0	7.367888e+05	1.391257e+06	0.0	75400.00	238000.0
Pop13	9247.0	6.933085e+05	1.311471e+06	0.0	71827.50	215000.0
Pop14	9229.0	6.476986e+05	1.235835e+06	0.0	65600.00	200000.0
Pop15	9247.0	6.029855e+05	1.163827e+06	0.0	58145.50	189300.0
Pop16	9229.0	5.551750e+05	1.076834e+06	0.0	50700.00	171647.0
Pop17	9247.0	4.962309e+05	9.725906e+05	0.0	42100.00	150315.0
Pop18	9229.0	4.322113e+05	8.448360e+05	0.0	36300.00	131900.0
Pop19	9247.0	3.605436e+05	7.152276e+05	0.0	27200.00	108452.0
Pop20	9185.0	2.912263e+05	5.999338e+05	0.0	20400.00	84700.0
Pop21	9091.0	2.142607e+05	4.641550e+05	0.0	13800.00	57300.0
Pop22	8227.0	1.415479e+05	3.203072e+05	0.0	10000.00	36400.0
Pop23	8227.0	9.110114e+04	2.438814e+05	0.0	5600.00	20422.0
Pop24	1168.0	3.567674e+04	9.200778e+04	0.0	3525.75	10761.0
Pop25	1168.0	9.541263e+03	2.991613e+04	0.0	760.75	2221.5
Pop26	9229.0	6.554370e+02	1.267577e+04	0.0	0.00	0.0
Lb	9157.0	1.695519e+05	3.115556e+05	1.0	22304.00	51994.0

	75%	max
Country	4220.00	5200.0
Admin1	901.00	902.0
Year	1998.00	2017.0
Sex	2.00	9.0
Frmat	2.00	9.0
Pop1	9663800.00	152967793.0
Pop2	193900.00	2800600.0
Pop3	334950.00	10850300.0

```
Pop4      181375.00   2070000.0
Pop5      181200.00   2094000.0
Pop6      181000.00   2132000.0
Pop7      940910.50   12773600.0
Pop8      923419.00   11614400.0
Pop9      880500.00   11495400.0
Pop10     814100.00   12696700.0
Pop11     763550.00   12484600.0
Pop12     701626.00   12027500.0
Pop13     645750.00   11387968.0
Pop14     602225.00   11592971.0
Pop15     544800.00   11535713.0
Pop16     482800.00   10695801.0
Pop17     414150.00   9535100.0
Pop18     358100.00   9065100.0
Pop19     298337.00   6574400.0
Pop20     243700.00   5692200.0
Pop21     176359.00   4409200.0
Pop22     110776.50   3529748.0
Pop23     61000.00    3628315.0
Pop24     27174.75    1023847.0
Pop25     6408.75     350675.0
Pop26     0.00        527000.0
Lb        195742.00   2876306.0
        count unique  top freq
SubDiv  138   6       A20  38
```

Out[36]:

	Country	Admin1	SubDiv	Year	Sex	Frmat	Pop1	Pop2	Pop3	Pop4	...	Pc
0	1060	NaN	NaN	1980	1	7	137100.0	3400.0	15800.0	NaN	...	NaN
1	1060	NaN	NaN	1980	2	7	159000.0	4000.0	18400.0	NaN	...	NaN
2	1125	NaN	NaN	1955	1	2	5051500.0	150300.0	543400.0	NaN	...	1102
3	1125	NaN	NaN	1955	2	2	5049400.0	145200.0	551000.0	NaN	...	1221
4	1125	NaN	NaN	1956	1	2	5353700.0	158700.0	576600.0	NaN	...	1169

5 rows × 33 columns

In [37]:

```
#merge mortality with country data to get country name - icd_country has a
ll the valid death data for all years
icd_country = pd.merge(mortality, country_codes, how='inner', on='Country'
)

#check merge didn't lose information - should have the same number of rows
 after merge with inner option
print(mortality.shape)
print(icd_country.shape)
```

```
(3704896, 39)
(3704896, 40)
```

Description of data:

Mortality data
For various countries mortality data are recorded for various years using ICD code. Age groups distribution of deaths are also included. Not every country reports on age groups in the same way, and not every country uses the same level of ICD coding system (e.g. ICD 9 versus ICD 10). For each country, for each year for which data exists, the total deaths for males and females for each recorded cause (ICD10 code) is reported. For rare causes of death, it is possible that there is a record just for males, or vice versa. The column DEATHS1 (which has no missing values) reports the total deaths in each case.

Country lookup data
This dataset contains one record per country by which the country name is looked up from a country code field that exists in the mortality data. There are no missing values in this dataset.

Population lookup data
For various countries population data are recorded for various years. For each year for which data exists, there are two records reporting population for Males and Females. The column POP1 (which has no missing values) reports the total population in each case.

1. Population and Total Number of Deaths (all causes) for selected countries in 2010

In [38]:
```
#keep only the mortality data we need for 3 countries and 2010 data only
mortality_subset = icd_country[ (icd_country['name'].isin(['Iceland','Ital
y','New Zealand'])) & (icd_country['Year'] == 2010)]
print(mortality_subset.name.unique())
print(mortality_subset.Year.unique())
print(mortality_subset.shape)
mortality_subset.head()
```

```
['Iceland' 'Italy' 'New Zealand']
[2010]
(7382, 40)
```

Out[38]:

	Country	Admin1	SubDiv	Year	List	Cause	Sex	Frmat	IM_Frmat	Deaths1	...	De
2612934	4160	NaN	NaN	2010	103	A04	2	0	1	1	...	1.0
2612935	4160	NaN	NaN	2010	103	A05	2	0	1	1	...	0.0
2612936	4160	NaN	NaN	2010	103	A39	1	0	1	1	...	0.0
2612937	4160	NaN	NaN	2010	103	A41	1	0	1	5	...	0.0
2612938	4160	NaN	NaN	2010	103	A41	2	0	1	3	...	0.0

5 rows × 40 columns

In [39]:
```
#merge with the population data
mortality_pop = pd.merge(mortality_subset, population, how='inner', on=['C
ountry','Year', 'Sex'])
mortality_pop.sort_values(by=['Country','Cause','Sex'], inplace=True)
```

```
#check merge didn't lose information - should have the same number of rows
 after merge with inner option
print(mortality_subset.shape)
print(mortality_pop.shape)
mortality_pop.head()
```

```
(7382, 40)
(7382, 70)
```

Out[39]:

	Country	Admin1_x	SubDiv_x	Year	List	Cause	Sex	Frmat_x	IM_Frmat	Deaths1	...	I
0	4160	NaN	NaN	2010	103	A04	2	0	1	1	...	7
1	4160	NaN	NaN	2010	103	A05	2	0	1	1	...	7
163	4160	NaN	NaN	2010	103	A39	1	0	1	1	...	7
164	4160	NaN	NaN	2010	103	A41	1	0	1	5	...	7
2	4160	NaN	NaN	2010	103	A41	2	0	1	3	...	7

5 rows × 70 columns

In [40]:

```
#check against above - correct population figures for Iceland 2010
pop_iceland_2010 = population[ (population['Country'] == 4160) & (populati
on['Year'] == 2010)]
pop_iceland_2010
```

Out[40]:

	Country	Admin1	SubDiv	Year	Sex	Frmat	Pop1	Pop2	Pop3	Pop4	...	Pop18
5951	4160	NaN	NaN	2010	1	0	159971.0	2529.0	2483.5	2412.0	...	7880.0
5952	4160	NaN	NaN	2010	2	0	158070.0	2409.0	2380.5	2271.0	...	7536.0

2 rows × 33 columns

In [41]:

```
#merge population data with country code to get country name
country_pop = pd.merge(population, country_codes, how='inner', on='Country
')
print(population.shape)
print(country_pop.shape)

#create a function to give pop and death data
def pop_deaths(country):
    pop = country_pop[(country_pop['name'] == country) & (country_pop['Yea
r'] == 2010)]
    total_pop = int(pop.groupby('Year')['Pop1'].sum().reset_index().iloc[0
]['Pop1'])
    death = mortality_pop[(mortality_pop['name'] == country)]
    total_death = death['Deaths1'].sum()
    print (country, " : Population - " + str(total_pop) + " Deaths - " + s
tr(total_death) + " Rate:", round(total_death/total_pop*100,2))

pop_deaths('Iceland')
```

```
pop_deaths('Italy')
pop_deaths('New Zealand')
```

```
(9383, 33)
(9383, 34)
Iceland  : Population - 318041 Deaths - 4038 Rate: 1.27
Italy  : Population - 60483386 Deaths - 1169230 Rate: 1.93
New Zealand  : Population - 4367360 Deaths - 57298 Rate: 1.31
```

Table 5 - Population and Deaths for selected countries, 2010

</center>

Country	**Population**	**Total Deaths**	**Death Rate**
Iceland	318,041	4,038	1.27%
Italy	60,483,386	1,169,230	1.93%
New Zealand	4,367,360	57,298	1.31%

Discussion - Population and Deaths for selected countries, 2010

For 2010, it appears that while Iceland and New Zealand have similar death rates, calculated as total deaths as a percentage of population (1.27% vs. 1.31% resprectively), Italy has a substantially higher death rate of 1.93%

2. Distribution of deaths by age group in Italy

In [42]:

```
#function to sum deaths by age group for a dataframe - assumes a format of
 00 - data in all age categories
def death_by_age(df):

    df = df.copy(deep=True)

    #keep only columns that have deaths split by age groups
    filter_col = [col for col in df if col.startswith('Deaths')]
    #drop the column that has deaths by all ages
    df = df[filter_col].drop('Deaths1', axis=1)

    #rename column names for subsequent display
    new_col_names = ['Deaths at age 0 year',\
    'Deaths at age 1 year',\
    'Deaths at age 2 years',\
    'Deaths at age 3 years',\
    'Deaths at age 4 years',\
    'Deaths at age 5-9 years',\
    'Deaths at age 10-14 years',\
    'Deaths at age 15-19 years',\
```

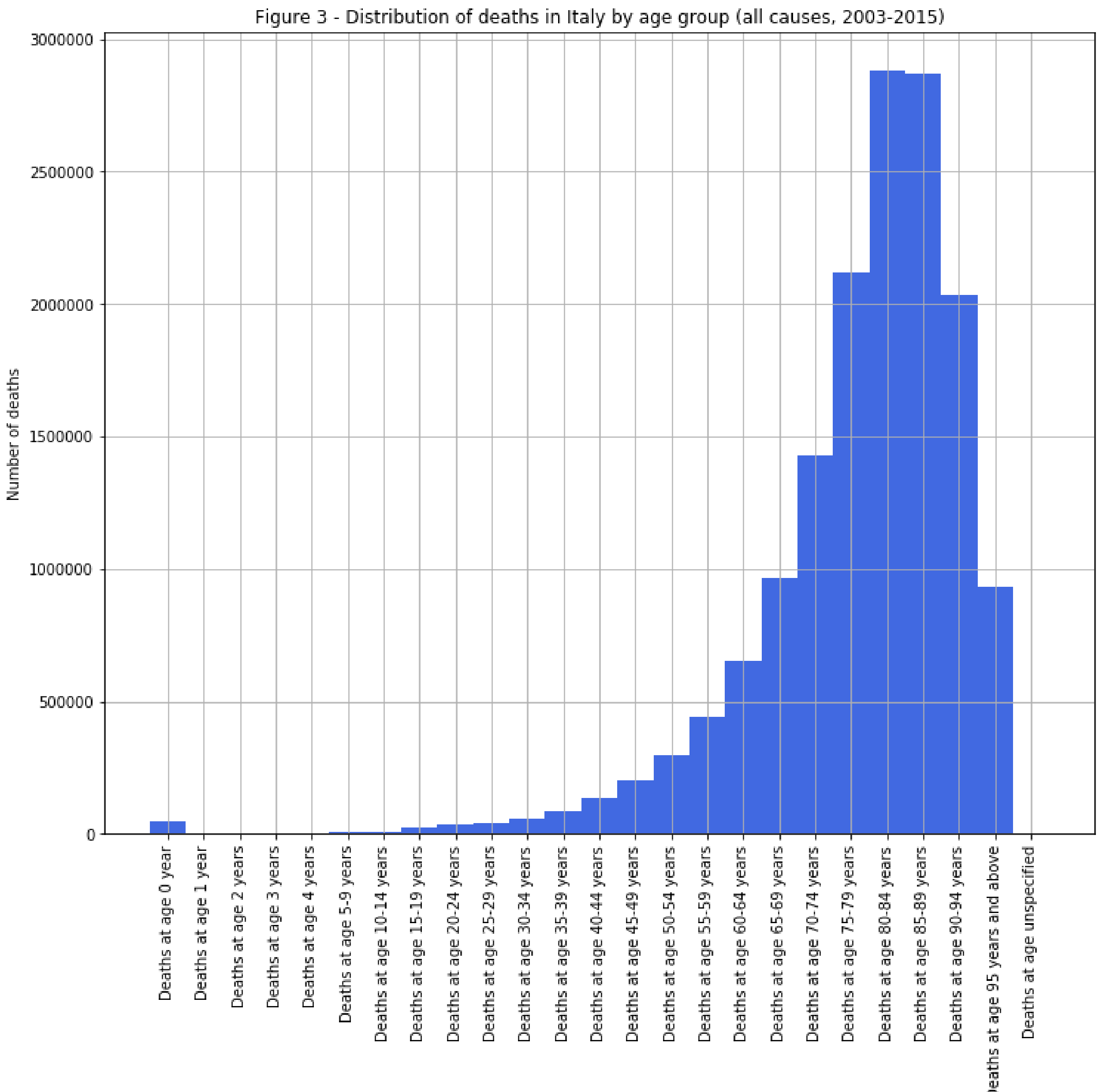
```
    'Deaths at age 20-24 years',\
    'Deaths at age 25-29 years',\
    'Deaths at age 30-34 years',\
    'Deaths at age 35-39 years',\
    'Deaths at age 40-44 years',\
    'Deaths at age 45-49 years',\
    'Deaths at age 50-54 years',\
    'Deaths at age 55-59 years',\
    'Deaths at age 60-64 years',\
    'Deaths at age 65-69 years',\
    'Deaths at age 70-74 years',\
    'Deaths at age 75-79 years',\
    'Deaths at age 80-84 years',\
    'Deaths at age 85-89 years',\
    'Deaths at age 90-94 years',\
    'Deaths at age 95 years and above' ,\
    'Deaths at age unspecified']

    df.columns = new_col_names
    df = df.sum(axis=0).reset_index()
    df.columns=['agegroup', 'numdeaths']

    return df
```

In [43]:

```
#get data for Italy - all years
italy_data = icd_country[icd_country['name'] == 'Italy']
print(italy_data.shape)

#check Italy data is right another way
italy_data2 = mortality[mortality['Country'] == 4180]
print(italy_data2.shape)

#check formats are consistent for this country
print(italy_data['Frmat'].value_counts())

#how many years
print(italy_data['Year'].value_counts().sort_index())


#use function defined above to get total deaths for all age groups
italy_death_data_all=death_by_age(italy_data)

#show graphically
fig = plt.figure(figsize=(12,10))
ax = fig.add_subplot(111)
ax.set_title("Figure 3 - Distribution of deaths in Italy by age group (all
 causes, 2003-2015)")
ax.bar(italy_death_data_all['agegroup'], italy_death_data_all['numdeaths']
, width=1.0, color="royalblue")
ax.set_ylabel("Number of deaths")
ax.grid(b=True)
plt.xticks(rotation=90)
plt.show()
```

```
(63356, 40)
(63356, 39)
0    63356
```

```
Name: Frmat, dtype: int64
2003    5018
2004    4909
2005    4824
2006    4845
2007    4838
2008    4903
2009    4999
2010    4970
2011    4884
2012    4910
2013    4876
2014    4643
2015    4737
Name: Year, dtype: int64
```



Discussion - Deaths by age group in Italy for all years

After a significant blip indicating infant mortality deaths (deaths of infants under 1 year old), the total number of deaths in Italy falls, then starts rising about age 15-19. From that point on the rise in total deaths from all causes is roughly exponential for each age-group with a growing number of deaths for each increasing age-group. This reaches a peak at the 80-89 years old age-groups before a sharp fall at the 90-94 age-group. This latter fall probably reflects the fact that the proportion of 90+ people in Italy (as in other countries) is quite small.

3. Top 5 Causes of death in Italy for Neoplasm category C00-D48

In [44]:

```
#function to get Neoplasm causes of death only
def get_neoplasms(df):

    df=df.copy(deep=True)

    #create new columns that split the ICD10 code into useful values for s
ubsequent checking
    df['first'] = df['Cause'].str[0]
    df['second_third'] = df['Cause'].str[1:3]
    df['second_third_num'] = df['second_third'].apply(lambda x: int(x) if
x.isdigit() else 9999)

    #get the data that relate to ICD codes C00-D48 - all codes starting wi
th C are Neoplasms, as are all starting from D00-D48
    df = df[(df['first'] == 'C') | ( (df['first'] == 'D') & (df['second_th
ird_num'] < 49))]
    return df
```

In [45]:

```
#suppress non-useful warning
pd.options.mode.chained_assignment = None
pd.set_option('display.max_colwidth', -1)

#use function defined earlier to get Neoplasm deaths for Italy (all years)
italy_neoplasm_deaths = get_neoplasms(italy_data)

#check we have got all the neoplasm deaths
#print(italy_neoplasm_deaths.Cause)

#sum all Neoplasm deaths by ICD-10 code
italy_neoplasm_count = italy_neoplasm_deaths.groupby('Cause')['Deaths1'].s
um().reset_index()
italy_neoplasm_count.sort_values('Deaths1', ascending=False, inplace=True)


#originally a lookup file was used to lookup the description, but this see
med inaccurate
#therefore the following code was replaced by a manual lookup

# #get an ICD code-lookup file - obtained from http://www.cms.hhs.gov/ICD1
0/downloads/Dxgem_2009.zip
# #merge with Italian neoplasm count to get ICD terms (descriptions)
# icd_lookup=pd.read_csv("C:/DMHR assignment/ICD10/ICD10_lookup.csv")
# icd_lookup.columns = ['temp','description']
```

```
# icd_lookup['Cause'] = icd_lookup['temp'].str[0:4]
# icd_lookup.drop_duplicates(['Cause'], inplace=True)
# icd_lookup.drop('temp', axis=1, inplace=True)

# #merge to get ICD description term - this is not perfect due to lookup f
ile
# italy_neoplasm_count_icd = pd.merge(italy_neoplasm_count, icd_lookup, ho
w='left', on='Cause')

# #check merge
# print(italy_neoplasm_count.shape)
# print(italy_neoplasm_count_icd.shape)
# print(italy_neoplasm_count_icd.head())


#ICD description manually set
italy_neoplasm_count['icd_desc'] = "Other"
italy_neoplasm_count.iloc[0,2] = "Malignant neoplasm of unspecified part o
f unspecified bronchus or lung"
italy_neoplasm_count.iloc[1,2] = "Malignant neoplasm of breast of unspecif
ied site"
italy_neoplasm_count.iloc[2,2] = "Malignant neoplasm of colon, unspecified
"
italy_neoplasm_count.iloc[3,2] = "Malignant neoplasm of stomach, unspecifi
ed"
italy_neoplasm_count.iloc[4,2] = "Malignant neoplasm of pancreas, unspecif
ied"

#Split the dataset into top 5 and the rest
top = italy_neoplasm_count[italy_neoplasm_count['Deaths1'] >= italy_neopla
sm_count.iloc[4,1]]
bottom = italy_neoplasm_count[italy_neoplasm_count['Deaths1'] < italy_neop
lasm_count.iloc[4,1]]
print(top.shape)
print(bottom.shape)

#sum the bottom category and append to top
other_total = bottom["Deaths1"].sum()
other_df = {'Cause': "Other", 'Deaths1': other_total, 'icd_desc': "Other n
eoplasms"}
italy_neoplasm_count_group = top.append(other_df, ignore_index=True)

#get the proportion of total
italy_neoplasm_count_group['percent'] = italy_neoplasm_count_group['Deaths
1'].apply(lambda x: (x/sum(italy_neoplasm_count_group['Deaths1'])) *100)
italy_neoplasm_count_group.head(10)
```

```
(5, 3)
(615, 3)
```

Out[45]:

	Cause	Deaths1	icd_desc	percent
0	C349	426451	Malignant neoplasm of unspecified part of unspecified bronchus or lung	18.964664
1	C509	155895	Malignant neoplasm of breast of unspecified site	6.932792

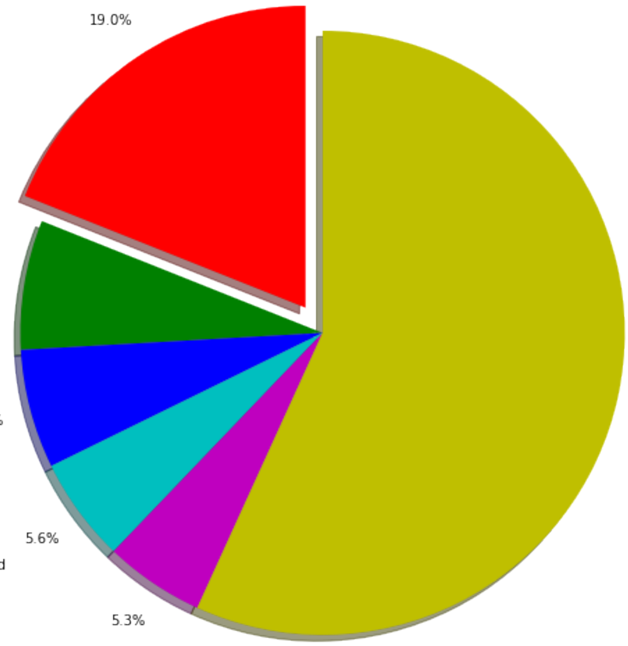
2	C189	143188	Malignant neoplasm of colon, unspecified	6.367701
3	C169	125679	Malignant neoplasm of stomach, unspecified	5.589059
4	C259	120070	Malignant neoplasm of pancreas, unspecified	5.339622
5	Other	1277378	Other neoplasms	56.806162

Table 6 - Deaths from Neoplasm in Italy (2003-2015)

ICD10 Code	**Description**	**Total Deaths**	**% of Neoplasm deaths**
C349	Malignant neoplasm of unspecified part of unspecified bronchus or lung	426,451	19.0%
C509	Malignant neoplasm of breast of unspecified site	155,895	6.9%
C189	Malignant neoplasm of colon, unspecified	143,188	6.4%
C169	Malignant neoplasm of stomach, unspecified	125,679	5.6%
C259	Malignant neoplasm of pancreas, unspecified	120070	5.3%
Other	All other neoplasms	1,277,378	56.8%

In [46]:
```
#create a piechart to visualise the table above
fig = plt.figure(figsize=(12,10))
ax = fig.add_subplot(111)
#colours = ['#C7B299', '#A67C52', '#C69C6E', '#754C24', '#534741', '#754C2
4']
colours=list('rgbcmy')
explode = [0.1, 0, 0, 0, 0, 0]
ax.axis('equal')
ax.pie(italy_neoplasm_count_group['percent'], colors=colours, shadow=True,
 startangle=90,
       explode=explode, labels=italy_neoplasm_count_group['icd_desc'], aut
opct='%.1f%%',
       pctdistance=1.15, labeldistance=1.3)
ax.set_title("Figure 4 - Proportion of deaths from neoplasms for Italy (al
l years) - Top 5 and all other ")
plt.show()
```

Figure 4 - Proportion of deaths from neoplasms for Italy (all years) - Top 5 and all other



Discussion - Deaths from Neoplasm in Italy (2003-2015)

As can be seen in Table 6 and Figure 4 above, lung cancer is by far the most common cause of cancer death in Italy for the years 2003-2015 with a proportion of 19% of all cancer deaths, followed by breast cancer, colon cancer, stomach cancer and pancreatic cancer in that order. With the second largest cuase of cancer deaths, breast cancer, at about 7%, the difference between the first and second cause of death is quite dramatic. These top 5 cancer deaths make up about 43% of all cancer deaths in Italy. This has implications for which cancers are targeted for treatment research with limited resources available - if a focus is made on the top 5 death-causing cancers and especially, lung cancer, more lives could be saved than targeting other "lesser" neoplasms.

4. Deaths by age group for Neoplasms in Australia, 2010

In [47]:

```
#get Neoplasm deaths data for Australia in 2010
australia_data_2010 = icd_country[(icd_country['name'].isin(['Australia'])
) & (icd_country['Year'] == 2010)]

#use function defined earlier to get Neoplasm deaths for Australia (2010)
australia_neoplasm_deaths_2010 = get_neoplasms(australia_data_2010)

#check we have got all the neoplasm deaths
#print(australia_neoplasm_deaths_2010.Cause)

#use function defined earlier to sum deaths by age groups
australia_neoplasm_deaths_2010_age=death_by_age(australia_neoplasm_deaths_
2010)
```

```
ordered = australia_neoplasm_deaths_2010_age.sort_values('numdeaths', asce
nding=False)
print(ordered.head(5))
```

```
                         agegroup  numdeaths
20  Deaths at age 80-84 years     7167.0
19  Deaths at age 75-79 years     6291.0
18  Deaths at age 70-74 years     5713.0
21  Deaths at age 85-89 years     5520.0
17  Deaths at age 65-69 years     4768.0
```

Table 7 - Top 5 age groups dying from Neoplasms in Australia, 2010

Age group	**Number of deaths**
Deaths at age 80-84 years	7167
Deaths at age 75-79 years	6291
Deaths at age 70-74 years	5713
Deaths at age 85-89 years	5520
Deaths at age 65-69 years	4768

Discussion - Top 5 age groups dying from Neoplasms in Australia, 2010

Looking at table 7 above, as one might expect the top 5 age-groups dying from cancer in Australia in terms of total numbers are in the elderly age-group ranging from 65-89. There is a marked fall in total deaths from cancer after the age of 84, with cancer deaths falling in the next age-group 85-89. This pattern is slightly different to what we found above in the pattern of all deaths in Italy where the total deaths fell markedly only in the next age-group 90-94 (Fig. 3 above). It may be worth investigating this anomaly - perhaps the proportion of deaths by different causes changes from the age-groups 85-89 to 90-94.

5. Comparing frequency of Neoplasm deaths in Italy and Australia, 2010

In [48]:

```
#get Neoplasm deaths data for Italy in 2010
italy_data_2010 = icd_country[(icd_country['name'].isin(['Italy'])) & (icd
_country['Year'] == 2010)]

#check format is the same - age groups reported the same
print(italy_data_2010['Frmat'].value_counts())
print(australia_data_2010['Frmat'].value_counts())

#use function defined earlier to get Neoplasm deaths for Italy (2010)
italy_neoplasm_deaths_2010 = get_neoplasms(italy_data_2010)
```

```
#check we have got all the neoplasm deaths
#print(italy_neoplasm_deaths_2010.Cause)

#use function defined earlier to sum deaths by age groups
italy_neoplasm_deaths_2010_age=death_by_age(italy_neoplasm_deaths_2010)

#get population data for 2010 for Australia and Italy and append to datafr
ame to get death rates per age group
italy_pop_2010 = country_pop[(country_pop['name'] == 'Italy') & (country_p
op['Year'] == 2010)]['Pop1'].sum()
australia_pop_2010 = country_pop[(country_pop['name'] == 'Australia') & (c
ountry_pop['Year'] == 2010)]['Pop1'].sum()

#overall deathrate for each country - total neoplasms divided by populatio
n
italy_neoplasm_deaths_2010_age['pop'] = italy_pop_2010
italy_neoplasm_deaths_2010_age['deathrate'] = italy_neoplasm_deaths_2010_a
ge['numdeaths']/italy_neoplasm_deaths_2010_age['pop']*100

australia_neoplasm_deaths_2010_age['pop'] = australia_pop_2010
australia_neoplasm_deaths_2010_age['deathrate'] = australia_neoplasm_death
s_2010_age['numdeaths']/australia_neoplasm_deaths_2010_age['pop']*100

italy_neoplasm_deaths_2010.head()
```

```
0    4970
Name: Frmat, dtype: int64
0    3777
Name: Frmat, dtype: int64
```

Out[48]:

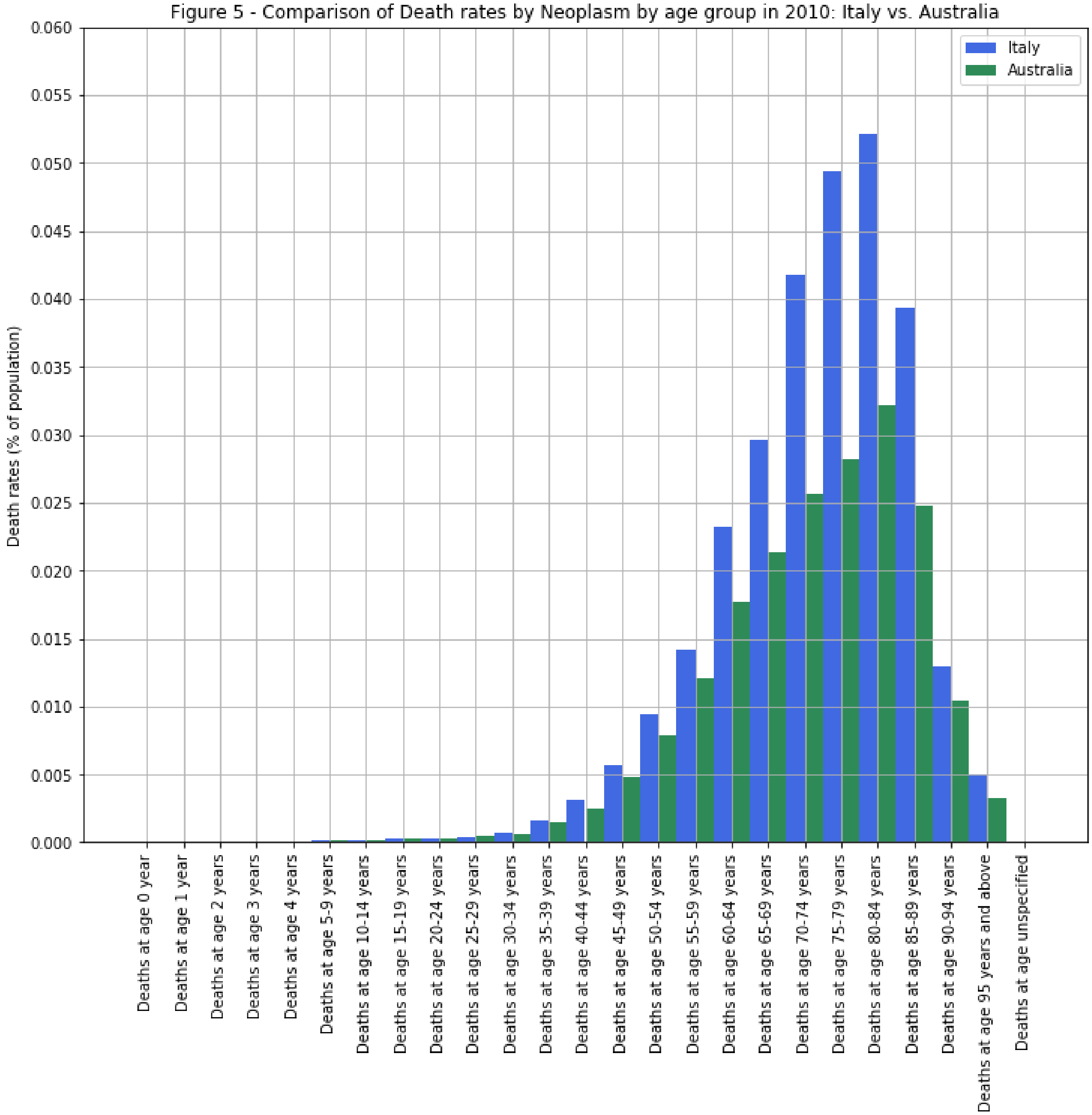
	Country	Admin1	SubDiv	Year	List	Cause	Sex	Frmat	IM_Frmat	Deaths1	...	De
2652668	4180	NaN	NaN	2010	104	C000	1	0	1	3	...	0.0
2652669	4180	NaN	NaN	2010	104	C000	2	0	1	4	...	2.0
2652670	4180	NaN	NaN	2010	104	C001	1	0	1	17	...	1.0
2652671	4180	NaN	NaN	2010	104	C001	2	0	1	10	...	0.0
2652672	4180	NaN	NaN	2010	104	C006	1	0	1	1	...	0.0

5 rows × 43 columns

In [49]:

```
#create side by side bar plots for age related Neoplasm death rates (% of
population), Italy versus Australia 2010
N = 25
index = np.arange(N)
width = 0.5       # the width of the bars

fig = plt.figure(figsize=(12,10))
ax = fig.add_subplot(111)
rects1 = ax.bar(index, italy_neoplasm_deaths_2010_age['deathrate'], width,
 color='royalblue')
rects2 = ax.bar(index + width, australia_neoplasm_deaths_2010_age['deathra
te'], width, color='seagreen')
```

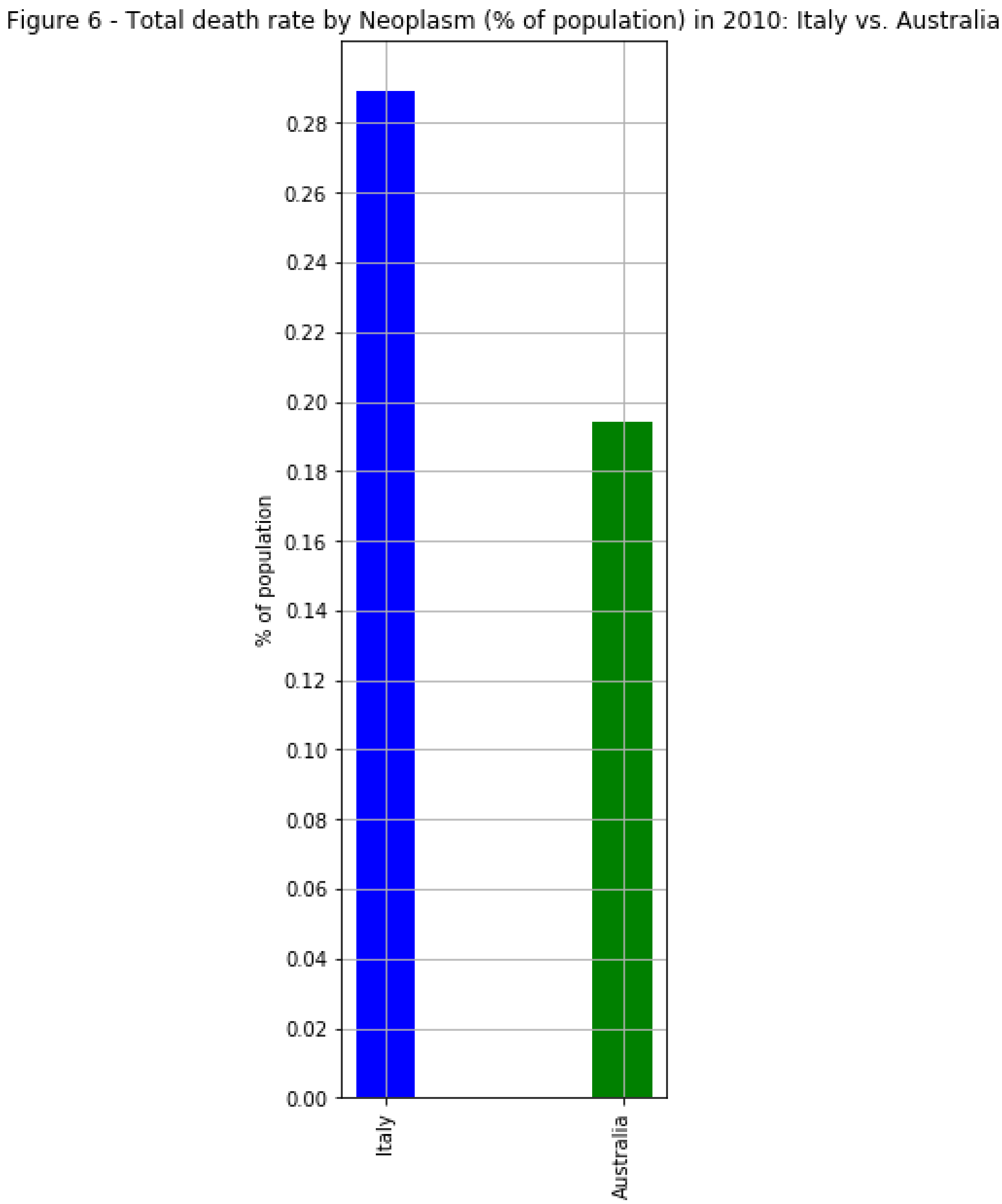
```
ax.set_ylabel('Death rates (% of population)')
ax.set_title('Figure 5 - Comparison of Death rates by Neoplasm by age grou
p in 2010: Italy vs. Australia')
ax.set_xticks(index + width / 2)
ax.set_xticklabels( ('Deaths at age 0 year',\
    'Deaths at age 1 year',\
    'Deaths at age 2 years',\
    'Deaths at age 3 years',\
    'Deaths at age 4 years',\
    'Deaths at age 5-9 years',\
    'Deaths at age 10-14 years',\
    'Deaths at age 15-19 years',\
    'Deaths at age 20-24 years',\
    'Deaths at age 25-29 years',\
    'Deaths at age 30-34 years',\
    'Deaths at age 35-39 years',\
    'Deaths at age 40-44 years',\
    'Deaths at age 45-49 years',\
    'Deaths at age 50-54 years',\
    'Deaths at age 55-59 years',\
    'Deaths at age 60-64 years',\
    'Deaths at age 65-69 years',\
    'Deaths at age 70-74 years',\
    'Deaths at age 75-79 years',\
    'Deaths at age 80-84 years',\
    'Deaths at age 85-89 years',\
    'Deaths at age 90-94 years',\
    'Deaths at age 95 years and above' ,\
    'Deaths at age unspecified') )

ax.legend( (rects1[0], rects2[0]), ('Italy', 'Australia'))
ax.grid(b=True)
plt.yticks(np.arange(0, max(italy_neoplasm_deaths_2010_age['deathrate']+.0
1), 0.005))
plt.xticks(rotation=90)
plt.show()
```



In [50]:

```
#find out total death rate for Neoplasm (% of population), Italy versus Au
stralia, 2010

total_italy_neoplasm_2010 = italy_neoplasm_deaths_2010['Deaths1'].sum()
total_australia_neoplasm_2010 = australia_neoplasm_deaths_2010['Deaths1'].
sum()

total_deaths_2010 = pd.DataFrame(columns=['country','tot_neoplasm_deaths_2
010','pop_2010'])
total_deaths_2010.loc[1] = ['Italy', total_italy_neoplasm_2010, italy_pop_
2010]
total_deaths_2010.loc[2] = ['Australia', total_australia_neoplasm_2010, au
stralia_pop_2010]
total_deaths_2010['total_rate'] = total_deaths_2010['tot_neoplasm_deaths_2
010']/total_deaths_2010['pop_2010']*100

fig = plt.figure(figsize=(3,10))
ax = fig.add_subplot(111)
```

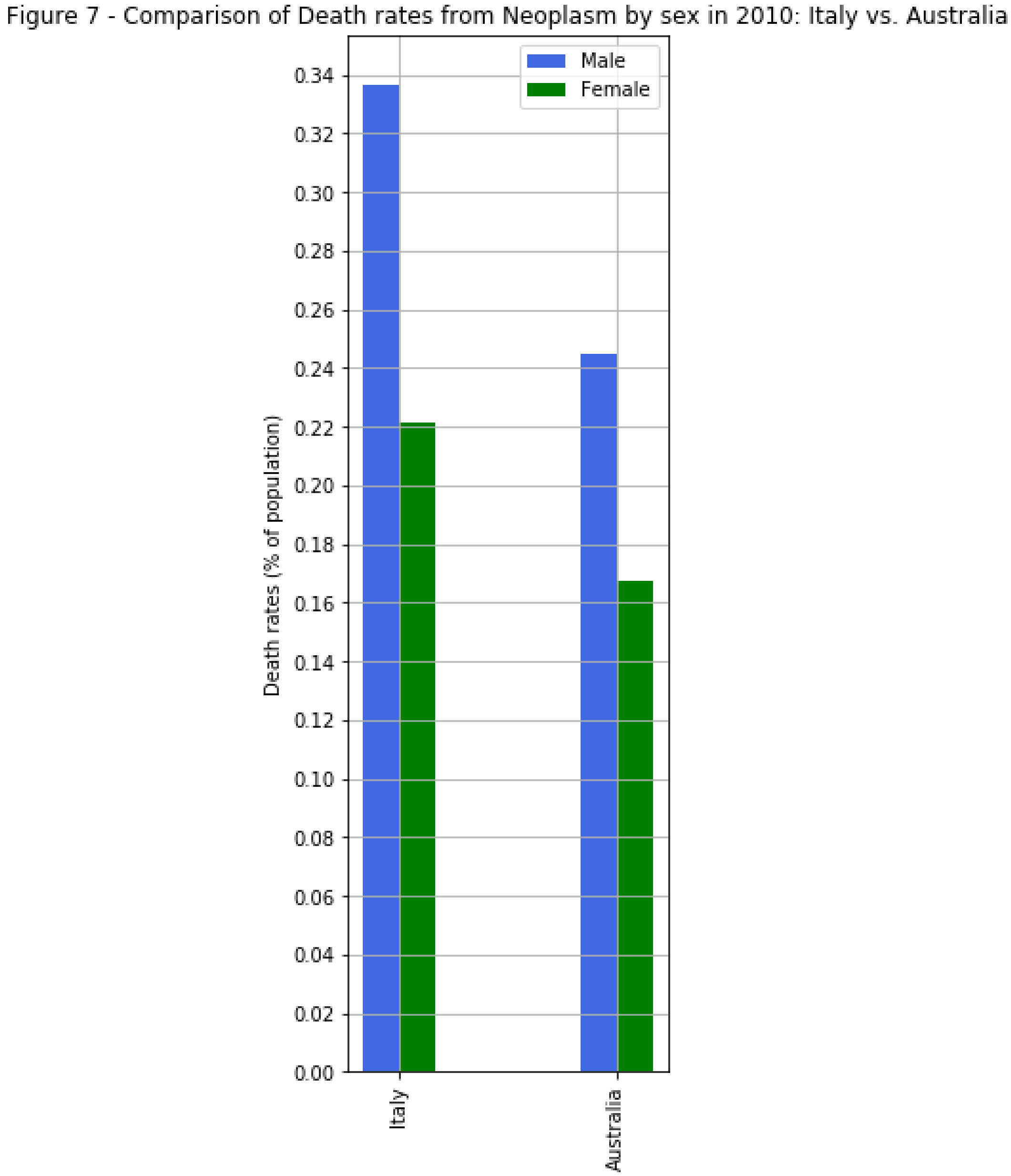
```
ax.set_title("Figure 6 - Total death rate by Neoplasm (% of population) in
 2010: Italy vs. Australia")
ax.bar(total_deaths_2010['country'], total_deaths_2010['total_rate'], colo
r=list('bgkym') ,width=0.25)
ax.grid(b=True)
ax.set_ylabel("% of population")
plt.yticks(np.arange(0, max(total_deaths_2010['total_rate']+.01), 0.02))
plt.xticks(rotation=90)
plt.show()
```



In [51]:

```
#death rate by sex for Italy and Australia

#italy
italy_deaths = pdsql("select name, Sex, sum(Deaths1) as deaths from italy_
neoplasm_deaths_2010 group by name, Sex order by Sex")
italy_pop = pdsql ("select name, Sex, Pop1 from country_pop where name='It
aly' and Year=2010")
italy_sex_rate =  pd.merge(italy_deaths, italy_pop, how='inner', on=['name
','Sex'])
```

```
italy_sex_rate['death_rate'] = italy_sex_rate['deaths']/italy_sex_rate['Po
p1']*100

#australia
australia_deaths = pdsql("select name, Sex, sum(Deaths1) as deaths from au
stralia_neoplasm_deaths_2010 group by name, Sex order by Sex")
australia_pop = pdsql ("select name, Sex, Pop1 from country_pop where name
='Australia' and Year=2010")
australia_sex_rate =  pd.merge(australia_deaths, australia_pop, how='inner
', on=['name','Sex'])
australia_sex_rate['death_rate'] = australia_sex_rate['deaths']/australia_
sex_rate['Pop1']*100

#create bar plot for sex differences

fig = plt.figure(figsize=(3,10))
ax = fig.add_subplot(111)
ax.set_ylabel('Death rates (% of population)')
ax.set_title('Figure 7 - Comparison of Death rates from Neoplasm by sex in
 2010: Italy vs. Australia')

index = np.array([0,3])
width = 0.5       # the width of the bars
rects1 = ax.bar(index, italy_sex_rate['death_rate'], width, color='royalbl
ue')
rects2 = ax.bar(index+width, australia_sex_rate['death_rate'], width, colo
r='green')

ax.set_xticks(index + width / 2)
ax.set_xticklabels( ('Italy', 'Australia') )
ax.legend( (rects1[0], rects2[0]), ('Male', 'Female'))
ax.grid(b=True)
plt.xticks(rotation=90)
plt.yticks(np.arange(0, max(italy_sex_rate['death_rate']+.01), 0.02))
plt.show()
```



In [52]:
```
#function to get top 5 causes of death
def top_5(df):

    df = df.copy(deep=True)

    df2 = df.groupby('Cause')['Deaths1'].sum().reset_index()
    df2.sort_values('Deaths1', ascending=False, inplace=True)

    top = df2[df2['Deaths1'] >= df2.iloc[4,1]]
    bottom = df2[df2['Deaths1'] < df2.iloc[4,1]]
    print(top.shape)
    print(bottom.shape)

    #sum the bottom category and append to top
    other_total = bottom["Deaths1"].sum()
    other_df = {'Cause': "Other", 'Deaths1': other_total, 'icd_desc': "Oth
er neoplasms"}
    df4 = top.append(other_df, ignore_index=True)
```

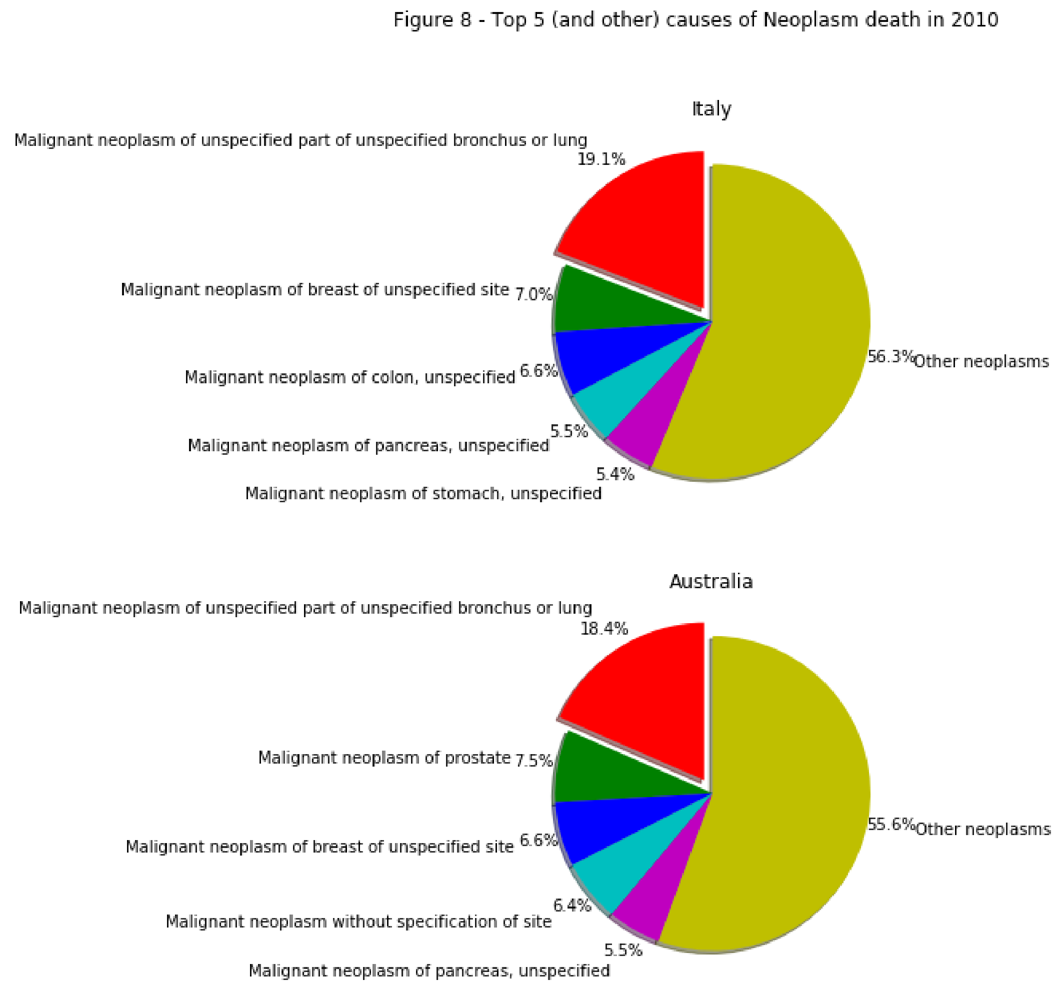
```
    #get the proportion of total
    df4['percent'] = df4['Deaths1'].apply(lambda x: (x/sum(df4['Deaths1']))*100)
    return df4
```

In [55]:
```
#Top 5 death causes from Neoplasm in Italy and Australia, 2010

#italy
#description looked up manually
italy_top5_2010 = top_5(italy_neoplasm_deaths_2010)
italy_top5_2010.iloc[0,2] = "Malignant neoplasm of unspecified part of unspecified bronchus or lung"
italy_top5_2010.iloc[1,2] = "Malignant neoplasm of breast of unspecified site"
italy_top5_2010.iloc[2,2] = "Malignant neoplasm of colon, unspecified"
italy_top5_2010.iloc[3,2] = "Malignant neoplasm of pancreas, unspecified"
italy_top5_2010.iloc[4,2] = "Malignant neoplasm of stomach, unspecified"

#australia
#description looked up manually
australia_top5_2010 = top_5(australia_neoplasm_deaths_2010)
australia_top5_2010.iloc[0,2] = "Malignant neoplasm of unspecified part of unspecified bronchus or lung"
australia_top5_2010.iloc[1,2] = "Malignant neoplasm of prostate"
australia_top5_2010.iloc[2,2] = "Malignant neoplasm of breast of unspecified site"
australia_top5_2010.iloc[3,2] = "Malignant neoplasm without specification of site"
australia_top5_2010.iloc[4,2] = "Malignant neoplasm of pancreas, unspecified"
```

```
(5, 2)
(444, 2)
(5, 2)
(331, 2)
```

In [56]:
```
#create side by side piecharts to visualise the data above
fig = plt.figure(figsize=(12,10))
axes1 = fig.add_subplot(211)
axes2 = fig.add_subplot(212)
#colours = ['#C7B299', '#A67C52', '#C69C6E', '#754C24', '#534741', '#754C24']
colours=list('rgbcmy')
explode = [0.1, 0, 0, 0, 0, 0]
axes1.axis('equal')

#italy
axes1.pie(italy_top5_2010['percent'], colors=colours, shadow=True, startangle=90,
        explode=explode, labels=italy_top5_2010['icd_desc'], autopct='%.1f%%',
        pctdistance=1.15, labeldistance=1.3)
axes1.set_title("Italy")

#australia
axes2.pie(australia_top5_2010['percent'], colors=colours, shadow=True, startangle=90,
```

```
        explode=explode, labels=australia_top5_2010['icd_desc'], autopct='%
.1f%%',
        pctdistance=1.15, labeldistance=1.3)
axes2.set_title("Australia")

fig.suptitle("Figure 8 - Top 5 (and other) causes of Neoplasm death in 201
0")

plt.show()
```



Discussion - Comparing frequency of Neoplasm deaths in Italy and Australia, 2010

In order to compare frequency of deaths between Australia and Italy (which have widely differing population numbers) in 2010, it was decided to calculate a death rate (number of deaths for relevant category as a precentage of total population in the country in 2010). Looking at Figure 5 above, it is clear that the death rates from cancer for all age-groups follows a similar pattern in both Italy and Australia. There is a rise of death rate with age-group until age 84, after which there is a sharp fall. However, the cancer death rate is lower for all age-groups in Australia (apart from age-group 25-29). This is also supported by Figure 6 above which shows the overall death rate from all cancers in 2010 for Italy vs. Australia (roughly 0.28% vs 0.19%).
Figure 7 shows the overall death rate from cancer for Italy and Australia split by sex. This reinforces the message from Figures 5 and 6. Australia has a lower death rate from cancer for both males and

females. In fact the death rate for Italian males from cancer in 2010 was twice that of Australian women (0.34% vs. 0.17%).

Any hypothesis that might propose that the higher overall death rate from cancer in Italy may be due to a population that is more skewed to the elderly would be contradicted by Figure 5, which shows that the death rate is lower for ALL age-groups.

Looking at Figure 8, which compares the top 5 causes of cancer deaths in the two countries, it can be seen that lung cancer accounts for the highest number of cancer deaths in both countries (18.4% for Australia, 19.1% for Italy). Breast cancer and pancreatic cancer are also in the top 5 cancer deaths for both countries. However prostrate cancer, which is the second largest cancer death cause in Australia, does not appear in the Italian top 5.

Comparing the death rates for the top-5 cancer deaths between the two countries is made challenging since there is such a large category for unspecified cancer in the Australian data, suggesting different recording mechanisms than Italy. It would definitely be worth finding out why that is. As suggested this data provides means for targeting the most common cancers, provided data on cause of death is correctly recorded.

Generally this latter issue points to the limitations of this data when comparing countries - different countries may use different protocols for recording deaths, and while this is not the case for Italy and Australia, may report age groups differently and may even use different revisions of the ICD codes.