# CorrTest_household_personalIncome

September 12, 2021

## 1 The affluence variable

This markdown contains the following:

- Correlation between personal and household income categories
- Investigating household 'affluence' in different regions
- Preparing the personal income affluence indicator for the models

Set up the environment

[2]:
```
import pandas as pd
from pandas import read_csv
import numpy as np
from sklearn.linear_model import LinearRegression
from numpy import cov
from scipy.stats import pearsonr
from scipy.stats import spearmanr
import matplotlib.pyplot as plt
import seaborn as sn


pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
```

Read in the household and personal income files

[93]:
```
# Group D
groupD=pd.read_csv("CompleteSet_GroupD.csv")
groupD=groupD.drop("Unnamed: 0",axis=1)
#Strip all leading whitespace in Area column
groupD['Area'] = groupD['Area'].apply(lambda x: x.strip())

#Remove total NZ row
groupD = groupD.loc[(groupD['Area'] != "Total - New Zealand by Regional Council/
↪SA2")]
#Remove total regions
groupD = groupD.loc[(groupD['ParentArea'] != "NewZealand")]

#Keep only 2013 and 2018
```

```
#groupD = groupD.loc[(groupD['Year'] == 2013) | (groupD['Year']==2018)]

groupD = groupD.drop([ 'less5k_Wholesale', 'less5k_Retail',
                      'less5k_TransPostWare', 'bet5k10k_Wholesale',
                      'bet5k10k_Retail', 'bet5k10k_TransPostWare',
                      'bet10k20k_Wholesale', 'bet10k20k_Retail',␣
 ↪'bet10k20k_TransPostWare',
                       'bet20k30k_Wholesale', 'bet20k30k_Retail',
                      'bet20k30k_TransPostWare', 'bet30k50k_Wholesale',
                      'bet30k50k_Retail', 'bet30k50k_TransPostWare',
                      'bet50k70k_Wholesale', 'bet50k70k_Retail',␣
 ↪'bet50k70k_TransPostWare', 'greater70k_Wholesale', 'greater70k_Retail',
                      'greater70k_TransPostWare', 'totStated_Wholesale',
                      'totStated_Retail', 'totStated_TransPostWare',
                      'notStated_Wholesale', 'notStated_Retail',␣
 ↪'notStated_TransPostWare'], axis=1)

groupD['Perc_Cat']=-99

print(groupD.shape)

# Group G
groupG=pd.read_csv("CompleteSet_GroupG.csv")
groupG=groupG.drop("Unnamed: 0",axis=1)
#Strip all leading whitespace in Area column
groupG['Area'] = groupG['Area'].apply(lambda x: x.strip())


#Remove total NZ row
groupG = groupG.loc[(groupG['Area'] != "Total - New Zealand by Regional Council/
 ↪SA2")]
#Remove total regions
groupG = groupG.loc[(groupG['ParentArea'] != "NewZealand")]

print(groupG.shape)
```

```
(6759, 13)
(4506, 14)
```

### 1.0.1 Correlation between personal and household income categories

Household income per SA2 level is only available for 2013 and 2018. It is important for this project to add the 2006 timestamp as well. Personal incomeper SA2 is available for 2006, 2013, and 2018. Therefore, we want to investigate whether we can use personal income as a proxy for household income.

There are 7 categories in both the personal income and household income data.

| Category | Personal income | Household income |
|---|---|---|
| cat1 | less5k | less20k |
| cat2 | between5k10k | between20k30k |
| cat3 | between10k20k | between30k50k |
| cat4 | between20k30k | between50k70k |
| cat5 | between30k50k | between70k100k |
| cat6 | between50k70k | between100k150k |
| cat7 | greater 70k | greater150k |

First we visually inspect the correlations between the categories.

[4]:
```
#Preparing the data
cat1_house_2013 = np.array(groupG.loc[(groupG['Year'] == 2013)].less20k.
 ↪tolist())
cat1_house_2013 = np.nan_to_num(cat1_house_2013,copy=False,nan=0.0)
cat2_house_2013 = np.array(groupG.loc[(groupG['Year'] == 2013)].bet20k_30k.
 ↪tolist())
cat2_house_2013 = np.nan_to_num(cat2_house_2013,copy=False,nan=0.0)
cat3_house_2013 = np.array(groupG.loc[(groupG['Year'] == 2013)].bet30k_50k.
 ↪tolist())
cat3_house_2013 = np.nan_to_num(cat3_house_2013,copy=False,nan=0.0)
cat4_house_2013 = np.array(groupG.loc[(groupG['Year'] == 2013)].bet50k_70k.
 ↪tolist())
cat4_house_2013 = np.nan_to_num(cat4_house_2013,copy=False,nan=0.0)
cat5_house_2013 = np.array(groupG.loc[(groupG['Year'] == 2013)].bet70k_100k.
 ↪tolist())
cat5_house_2013 = np.nan_to_num(cat5_house_2013,copy=False,nan=0.0)
cat6_house_2013 = np.array(groupG.loc[(groupG['Year'] == 2013)].bet100k_150k.
 ↪tolist())
cat6_house_2013 = np.nan_to_num(cat6_house_2013,copy=False,nan=0.0)
cat7_house_2013 = np.array(groupG.loc[(groupG['Year'] == 2013)].greater150k.
 ↪tolist())
cat7_house_2013 = np.nan_to_num(cat7_house_2013,copy=False,nan=0.0)

cat1_house_2018 = np.array(groupG.loc[(groupG['Year'] == 2018)].less20k.
 ↪tolist())
cat1_house_2018 = np.nan_to_num(cat1_house_2018,copy=False,nan=0.0)
cat2_house_2018 = np.array(groupG.loc[(groupG['Year'] == 2018)].bet20k_30k.
 ↪tolist())
cat2_house_2018 = np.nan_to_num(cat2_house_2018,copy=False,nan=0.0)
cat3_house_2018 = np.array(groupG.loc[(groupG['Year'] == 2018)].bet30k_50k.
 ↪tolist())
cat3_house_2018 = np.nan_to_num(cat3_house_2018,copy=False,nan=0.0)
cat4_house_2018 = np.array(groupG.loc[(groupG['Year'] == 2018)].bet50k_70k.
 ↪tolist())
cat4_house_2018 = np.nan_to_num(cat4_house_2018,copy=False,nan=0.0)
```

```
cat5_house_2018 = np.array(groupG.loc[(groupG['Year'] == 2018)].bet70k_100k.
 ↪tolist())
cat5_house_2018 = np.nan_to_num(cat5_house_2018,copy=False,nan=0.0)
cat6_house_2018 = np.array(groupG.loc[(groupG['Year'] == 2018)].bet100k_150k.
 ↪tolist())
cat6_house_2018 = np.nan_to_num(cat6_house_2018,copy=False,nan=0.0)
cat7_house_2018 = np.array(groupG.loc[(groupG['Year'] == 2018)].greater150k.
 ↪tolist())
cat7_house_2018 = np.nan_to_num(cat7_house_2018,copy=False,nan=0.0)

cat1_pers_2013 = np.array(groupD.loc[(groupD['Year'] == 2013)].less5k_TotInd.
 ↪tolist())
cat1_pers_2013 = np.nan_to_num(cat1_pers_2013,copy=False,nan=0.0)
cat2_pers_2013 = np.array(groupD.loc[(groupD['Year'] == 2013)].bet5k10k_TotInd.
 ↪tolist())
cat2_pers_2013 = np.nan_to_num(cat2_pers_2013,copy=False,nan=0.0)
cat3_pers_2013 = np.array(groupD.loc[(groupD['Year'] == 2013)].bet10k20k_TotInd.
 ↪tolist())
cat3_pers_2013 = np.nan_to_num(cat3_pers_2013,copy=False,nan=0.0)
cat4_pers_2013 = np.array(groupD.loc[(groupD['Year'] == 2013)].bet20k30k_TotInd.
 ↪tolist())
cat4_pers_2013 = np.nan_to_num(cat4_pers_2013,copy=False,nan=0.0)
cat5_pers_2013 = np.array(groupD.loc[(groupD['Year'] == 2013)].bet30k50k_TotInd.
 ↪tolist())
cat5_pers_2013 = np.nan_to_num(cat5_pers_2013,copy=False,nan=0.0)
cat6_pers_2013 = np.array(groupD.loc[(groupD['Year'] == 2013)].bet50k70k_TotInd.
 ↪tolist())
cat6_pers_2013 = np.nan_to_num(cat6_pers_2013,copy=False,nan=0.0)
cat7_pers_2013 = np.array(groupD.loc[(groupD['Year'] == 2013)].
 ↪greater70k_TotInd.tolist())
cat7_pers_2013 = np.nan_to_num(cat7_pers_2013,copy=False,nan=0.0)

cat1_pers_2018 = np.array(groupD.loc[(groupD['Year'] == 2018)].less5k_TotInd.
 ↪tolist())
cat1_pers_2018 = np.nan_to_num(cat1_pers_2018,copy=False,nan=0.0)
cat2_pers_2018 = np.array(groupD.loc[(groupD['Year'] == 2018)].bet5k10k_TotInd.
 ↪tolist())
cat2_pers_2018 = np.nan_to_num(cat2_pers_2018,copy=False,nan=0.0)
cat3_pers_2018 = np.array(groupD.loc[(groupD['Year'] == 2018)].bet10k20k_TotInd.
 ↪tolist())
cat3_pers_2018 = np.nan_to_num(cat3_pers_2018,copy=False,nan=0.0)
cat4_pers_2018 = np.array(groupD.loc[(groupD['Year'] == 2018)].bet20k30k_TotInd.
 ↪tolist())
cat4_pers_2018 = np.nan_to_num(cat4_pers_2018,copy=False,nan=0.0)
cat5_pers_2018 = np.array(groupD.loc[(groupD['Year'] == 2018)].bet30k50k_TotInd.
 ↪tolist())
```

```
cat5_pers_2018 = np.nan_to_num(cat5_pers_2018,copy=False,nan=0.0)
cat6_pers_2018 = np.array(groupD.loc[(groupD['Year'] == 2018)].bet50k70k_TotInd.
 ↪tolist())
cat6_pers_2018 = np.nan_to_num(cat6_pers_2018,copy=False,nan=0.0)
cat7_pers_2018 = np.array(groupD.loc[(groupD['Year'] == 2018)].
 ↪greater70k_TotInd.tolist())
cat7_pers_2018 = np.nan_to_num(cat7_pers_2018,copy=False,nan=0.0)
```

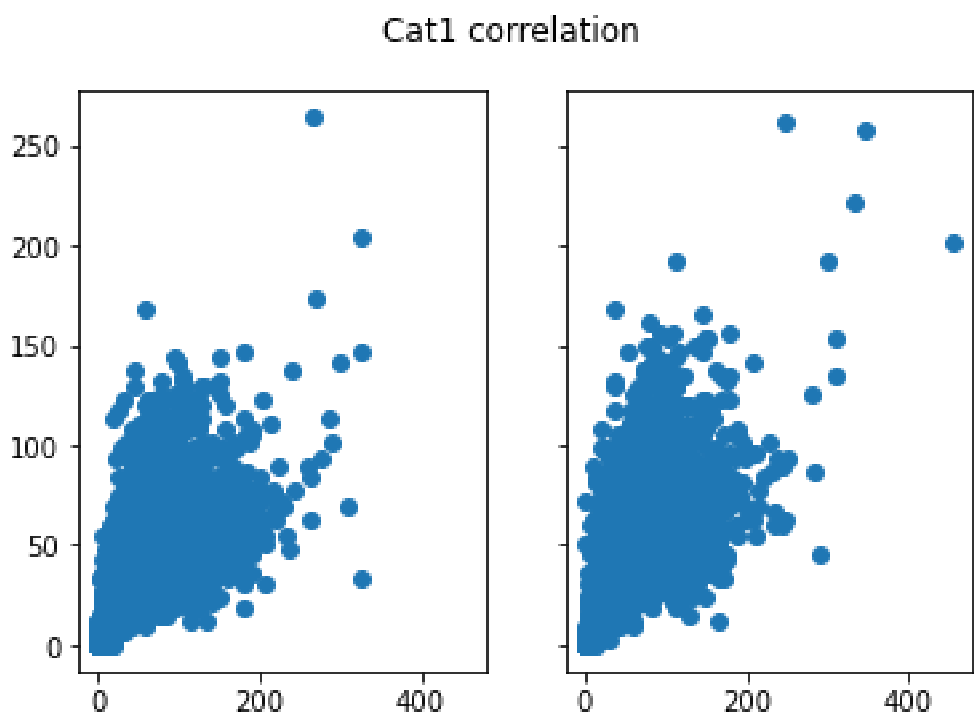
**Category 1 comparison** 2013 left pane, 2018 right pane

x - household

y - personal income

[25]:
```
fig, (ax1, ax2) = plt.subplots(1, 2,sharex=True,sharey=True)
fig.suptitle('Cat1 correlation')
ax1.scatter(cat1_house_2013, cat1_pers_2013)
ax2.scatter(cat1_house_2018, cat1_pers_2018)
```

[25]: <matplotlib.collections.PathCollection at 0x11a599760>




Not great evidence of correlation

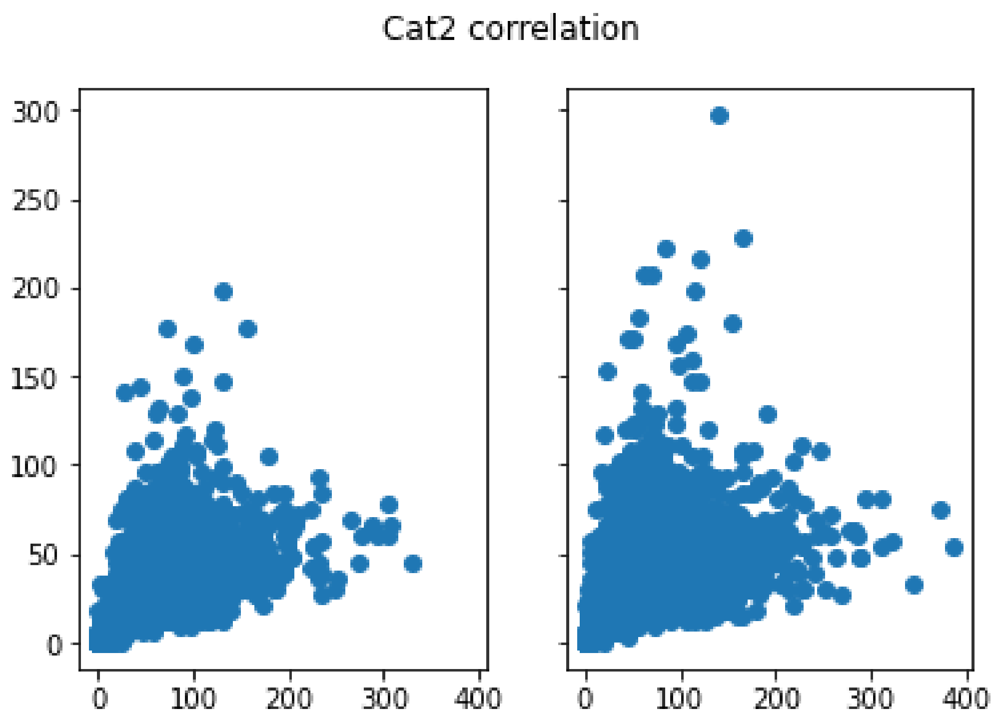
**Category 2 comparison** 2013 left pane, 2018 right pane

x - household

y - personal income

[26]:
```
fig, (ax1, ax2) = plt.subplots(1, 2,sharex=True,sharey=True)
fig.suptitle('Cat2 correlation')
ax1.scatter(cat2_house_2013, cat2_pers_2013)
ax2.scatter(cat2_house_2018, cat2_pers_2018)
```

[26]:
```
<matplotlib.collections.PathCollection at 0x11a56e220>
```




Not great evidence of correlation

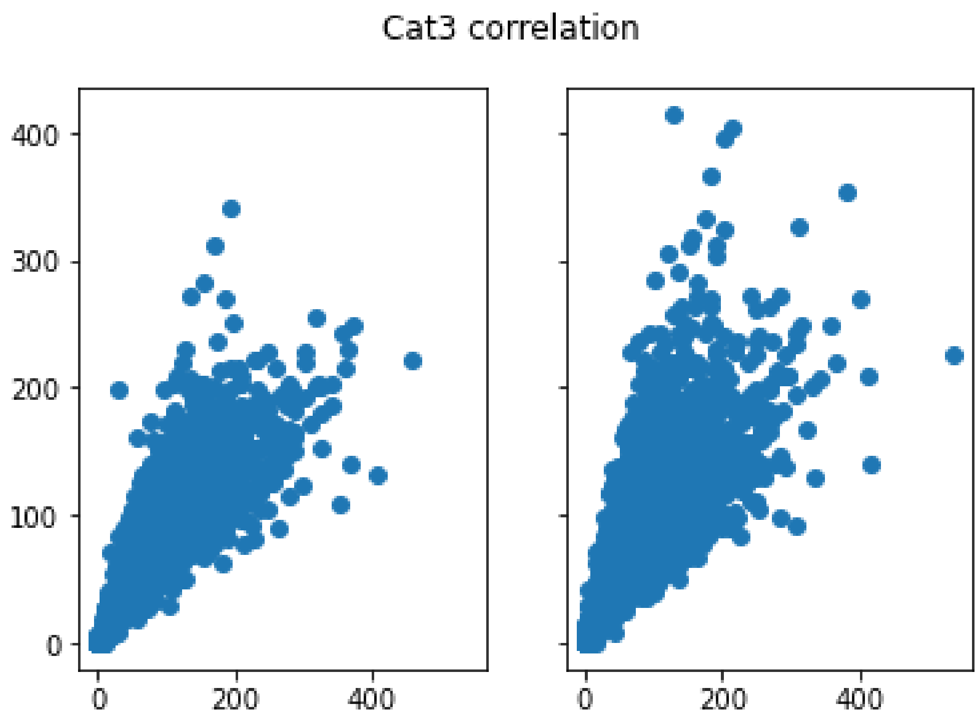
**Category 3 comparison** 2013 left pane, 2018 right pane

x - household

y - personal income

[27]:
```
fig, (ax1, ax2) = plt.subplots(1, 2,sharex=True,sharey=True)
fig.suptitle('Cat3 correlation')
ax1.scatter(cat3_house_2013, cat3_pers_2013)
ax2.scatter(cat3_house_2018, cat3_pers_2018)
```

[27]: <matplotlib.collections.PathCollection at 0x11a5ae3a0>




This is starting to look like something, but not convincing yet…

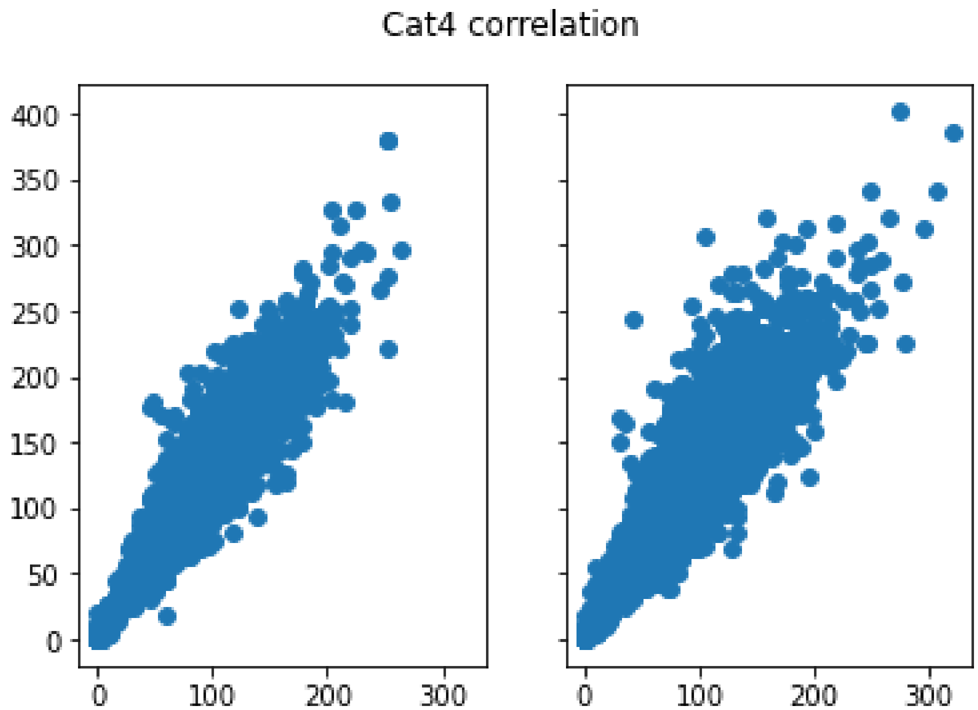
**Category 4 comparison** 2013 left pane, 2018 right pane

x - household

y - personal income

[28]:
```
fig, (ax1, ax2) = plt.subplots(1, 2,sharex=True,sharey=True)
fig.suptitle('Cat4 correlation')
ax1.scatter(cat4_house_2013, cat4_pers_2013)
ax2.scatter(cat4_house_2018, cat4_pers_2018)
```

[28]: <matplotlib.collections.PathCollection at 0x11ab05040>




This is starting to look like something.

[32]:
```
# Covariance

print("2013")
covariance = np.cov([cat4_pers_2013], [cat4_house_2013])
print(covariance)

# Pearson's correlation
corrP, _ = pearsonr(cat4_pers_2013, cat4_house_2013)
print('Pearsons correlation: %.3f' % corrP)

# Spearman's correlation
corrS, _ = spearmanr(cat4_pers_2013, cat4_house_2013)
print('Spearmans correlation: %.3f' % corrS)

print("2018")
covariance = np.cov([cat4_pers_2018], [cat4_house_2018])
print(covariance)

# Pearson's correlation
corrP, _ = pearsonr(cat4_pers_2018, cat4_house_2018)
print('Pearsons correlation: %.3f' % corrP)
```

```
# Spearman's correlation
corrS, _ = spearmanr(cat4_pers_2018, cat4_house_2018)
print('Spearmans correlation: %.3f' % corrS)
```

```
2013
[[3868.36143874 2856.73690911]
 [2856.73690911 2452.07337878]]
Pearsons correlation: 0.928
Spearmans correlation: 0.923
2018
[[4270.58390234 3035.37528766]
 [3035.37528766 2713.699943  ]]
Pearsons correlation: 0.892
Spearmans correlation: 0.890
```

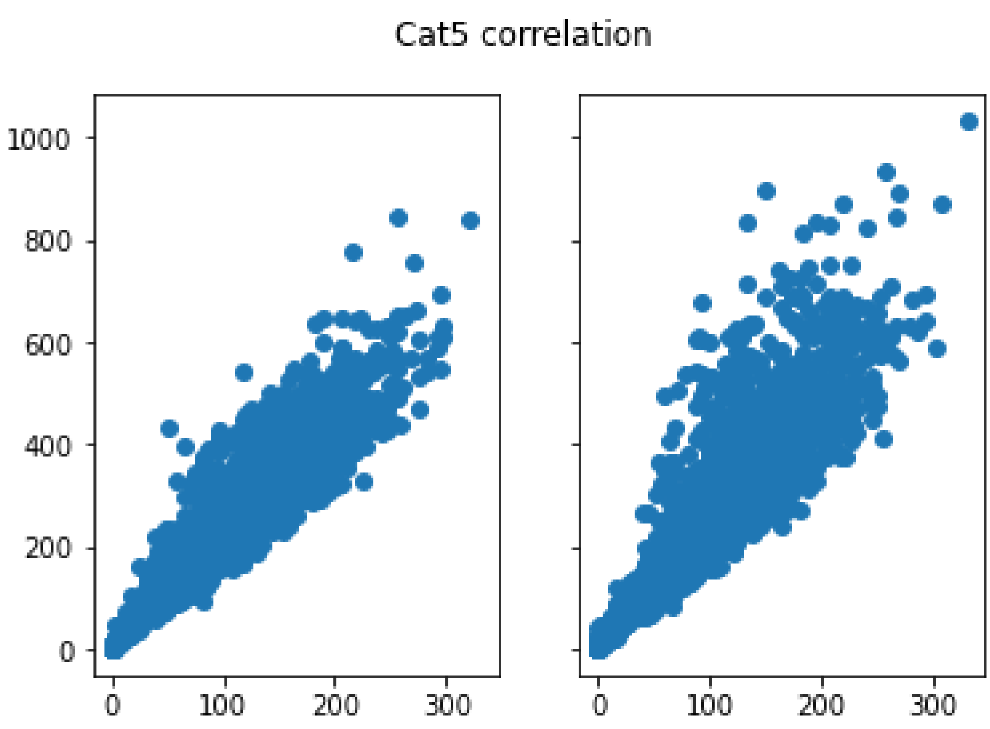
**Category 5 comparison** 2013 left pane, 2018 right pane

x - household

y - personal income

[29]:
```
fig, (ax1, ax2) = plt.subplots(1, 2,sharex=True,sharey=True)
fig.suptitle('Cat5 correlation')
ax1.scatter(cat5_house_2013, cat5_pers_2013)
ax2.scatter(cat5_house_2018, cat5_pers_2018)
```

[29]:
```
<matplotlib.collections.PathCollection at 0x11ac305e0>
```



The linear relation is tightening up.

[33]:
```
# Covariance

print("2013")
covariance = np.cov([cat5_pers_2013], [cat5_house_2013])
print(covariance)

# Pearson's correlation
corrP, _ = pearsonr(cat5_pers_2013, cat5_house_2013)
print('Pearsons correlation: %.3f' % corrP)

# Spearman's correlation
corrS, _ = spearmanr(cat5_pers_2013, cat5_house_2013)
print('Spearmans correlation: %.3f' % corrS)

print("2018")
covariance = np.cov([cat5_pers_2018], [cat5_house_2018])
print(covariance)

# Pearson's correlation
corrP, _ = pearsonr(cat5_pers_2018, cat5_house_2018)
print('Pearsons correlation: %.3f' % corrP)

# Spearman's correlation
corrS, _ = spearmanr(cat5_pers_2018, cat5_house_2018)
print('Spearmans correlation: %.3f' % corrS)
```

```
2013
[[20697.48207837  8360.83519842]
 [ 8360.83519842  3881.68318973]]
Pearsons correlation: 0.933
Spearmans correlation: 0.935
2018
[[27720.1182686   8900.68759948]
 [ 8900.68759948  3623.58380182]]
Pearsons correlation: 0.888
Spearmans correlation: 0.905
```

**Category 6 comparison** 2013 left pane, 2018 right pane

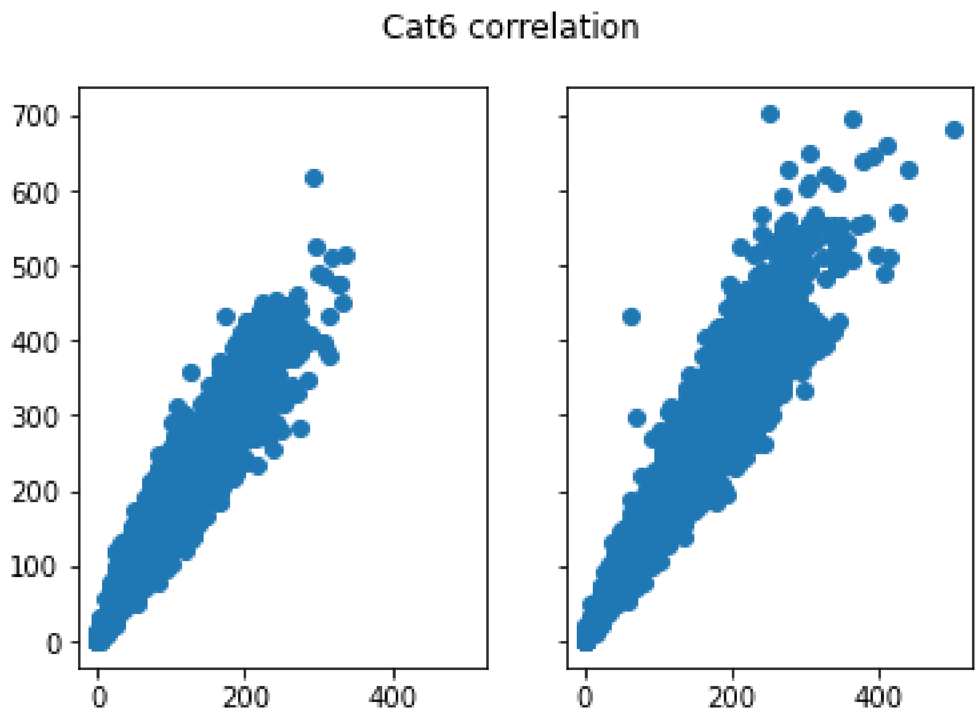
x - household

y - personal income

[30]:

```
fig, (ax1, ax2) = plt.subplots(1, 2,sharex=True,sharey=True)
fig.suptitle('Cat6 correlation')
ax1.scatter(cat6_house_2013, cat6_pers_2013)
ax2.scatter(cat6_house_2018, cat6_pers_2018)
```

[30]: <matplotlib.collections.PathCollection at 0x11ad8dd30>




There's a line...

[34]:

```
# Covariance

print("2013")
covariance = np.cov([cat6_pers_2013], [cat6_house_2013])
print(covariance)

# Pearson's correlation
corrP, _ = pearsonr(cat6_pers_2013, cat6_house_2013)
print('Pearsons correlation: %.3f' % corrP)

# Spearman's correlation
corrS, _ = spearmanr(cat6_pers_2013, cat6_house_2013)
print('Spearmans correlation: %.3f' % corrS)

print("2018")
```

```
covariance = np.cov([cat6_pers_2018], [cat6_house_2018])
print(covariance)

# Pearson's correlation
corrP, _ = pearsonr(cat6_pers_2018, cat6_house_2018)
print('Pearsons correlation: %.3f' % corrP)

# Spearman's correlation
corrS, _ = spearmanr(cat6_pers_2018, cat6_house_2018)
print('Spearmans correlation: %.3f' % corrS)
```

```
2013
[[10910.94214109  6555.33528297]
 [ 6555.33528297  4358.71521453]]
Pearsons correlation: 0.951
Spearmans correlation: 0.959
2018
[[17630.81355942 10268.88813317]
 [10268.88813317  6660.82567707]]
Pearsons correlation: 0.948
Spearmans correlation: 0.956
```

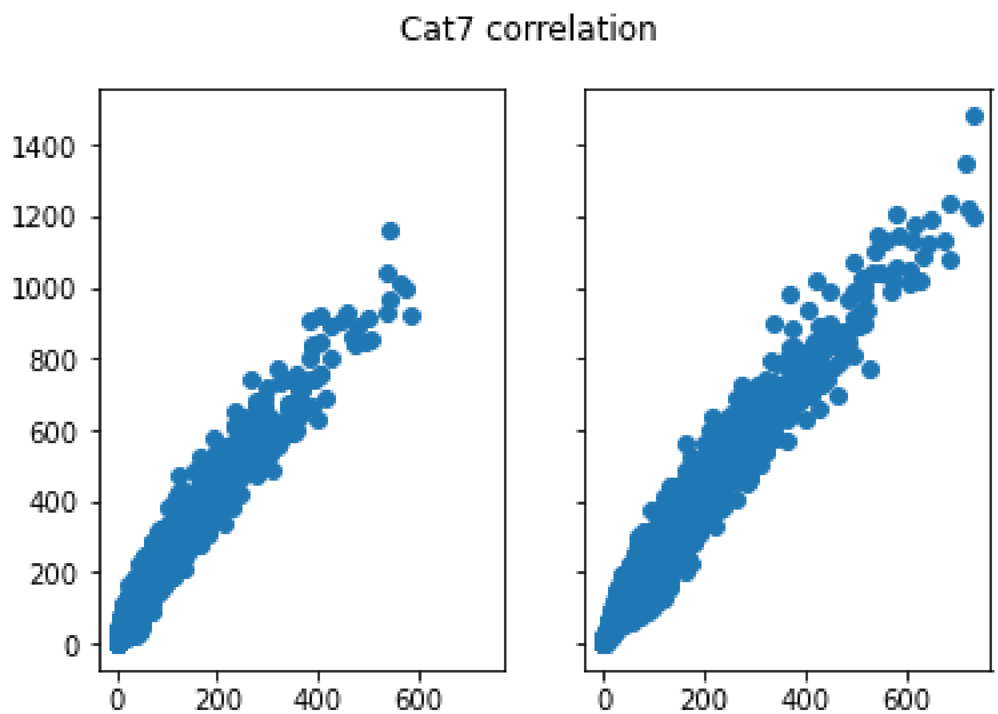
**Category 7 comparison** 2013 left pane, 2018 right pane

x - household

y - personal income

[31]:
```
fig, (ax1, ax2) = plt.subplots(1, 2,sharex=True,sharey=True)
fig.suptitle('Cat7 correlation')
ax1.scatter(cat7_house_2013, cat7_pers_2013)
ax2.scatter(cat7_house_2018, cat7_pers_2018)
```

[31]:
```
<matplotlib.collections.PathCollection at 0x11aef8d90>
```




That’s convincing.

[35]:
```
# Covariance

print("2013")
covariance = np.cov([cat7_pers_2013], [cat7_house_2013])
print(covariance)

# Pearson's correlation
corrP, _ = pearsonr(cat7_pers_2013, cat7_house_2013)
print('Pearsons correlation: %.3f' % corrP)

# Spearman's correlation
corrS, _ = spearmanr(cat7_pers_2013, cat7_house_2013)
print('Spearmans correlation: %.3f' % corrS)

print("2018")
covariance = np.cov([cat7_pers_2018], [cat7_house_2018])
print(covariance)

# Pearson's correlation
corrP, _ = pearsonr(cat7_pers_2018, cat7_house_2018)
print('Pearsons correlation: %.3f' % corrP)
```

```
# Spearman's correlation
corrS, _ = spearmanr(cat7_pers_2018, cat7_house_2018)
print('Spearmans correlation: %.3f' % corrS)
```

```
2013
[[28128.42417688 13418.13415801]
 [13418.13415801  6824.68569084]]
Pearsons correlation: 0.968
Spearmans correlation: 0.967
2018
[[50316.71805857 25831.09189583]
 [25831.09189583 13954.21735732]]
Pearsons correlation: 0.975
Spearmans correlation: 0.973
```

So what we are observing is that there is strong correlation between personal income and household income categories on the affluent side of the scale. So we can use personal income as a proxy for household income IF our variable is "affluence" and not "poverty"

### 1.0.2 Investigating household affluence in different regions

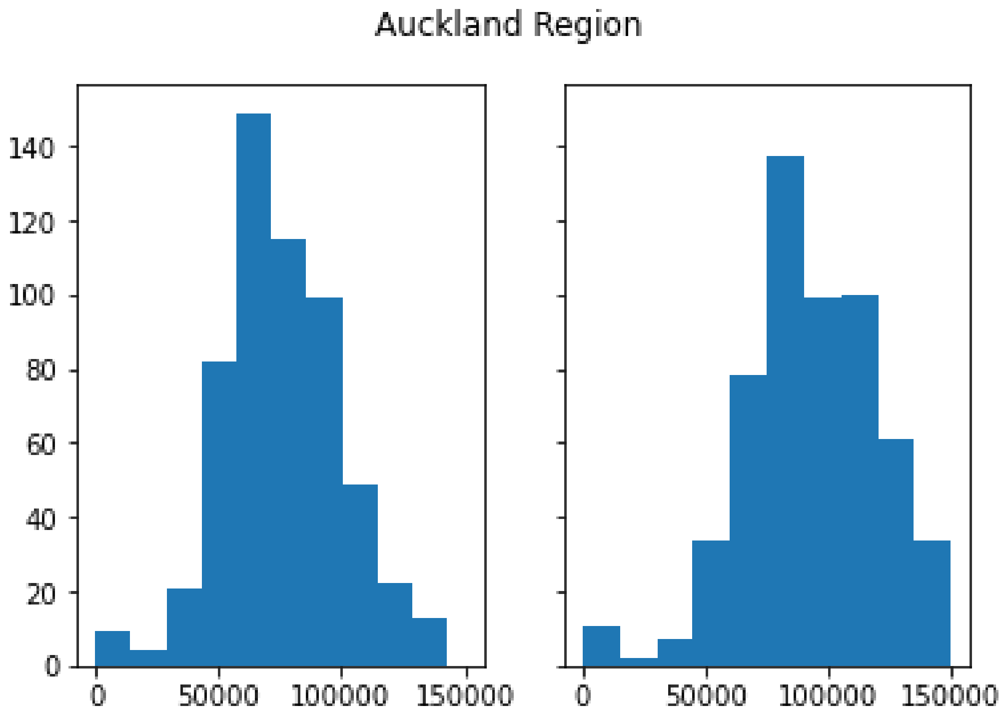
What constitutes "affluence" is different in different cities/regions. Here we want to differentiate between the category cut-off for affluence by region. To do that, we start with the histogram of median incomes per SA2 in each area.

Let's use Auckland as an illustration

[37]:
```
medHouseInc2013_Auck=np.array(groupG.loc[(groupG['Year'] ==␣
 ↪2013)&(groupG['ParentArea'] == 'AucklandRegion')].MedInc.tolist())
medHouseInc2013_Auck = np.nan_to_num(medHouseInc2013_Auck,copy=False,nan=0.0)

medHouseInc2018_Auck=np.array(groupG.loc[(groupG['Year'] ==␣
 ↪2018)&(groupG['ParentArea'] == 'AucklandRegion')].MedInc.tolist())
medHouseInc2018_Auck = np.nan_to_num(medHouseInc2018_Auck,copy=False,nan=0.0)

fig, (ax1, ax2) = plt.subplots(1, 2,sharex=True,sharey=True)
fig.suptitle('Auckland Region')
ax1.hist(medHouseInc2013_Auck)
ax2.hist(medHouseInc2018_Auck)

#80th percentile
print("80th percentile Auck 2013:",np.percentile(medHouseInc2013_Auck,80))
#determine in which category the 80th percentile falls
perc=np.percentile(medHouseInc2013_Auck,80)
if (perc > 50000) & (perc <= 70000):
    cat=4
elif (perc > 70000) & (perc <= 100000):
    cat=5
```

```
elif (perc > 100000) & (perc <= 150000):
    cat=6
elif (perc > 150000):
    cat=7
else:
    cat=-99
print("The 80th perc in 2013 was in category:",cat)

#80th percentile
print("80th percentile Auck 2018:",np.percentile(medHouseInc2018_Auck,80))
#determine in which category the 80th percentile falls
perc=np.percentile(medHouseInc2018_Auck,80)
if (perc > 50000) & (perc <= 70000):
    cat=4
elif (perc > 70000) & (perc <= 100000):
    cat=5
elif (perc > 100000) & (perc <= 150000):
    cat=6
elif (perc > 150000):
    cat=7
else:
    cat=-99
print("The 80th perc in 2018 was in category:",cat)

# add the cat to the groupD file

#groupD.loc[(groupD['Year'] == 2013)&(groupD['ParentArea'] ==
 ↪'AucklandRegion'),'Perc_Cat']=cat
```

```
80th percentile Auck 2013: 95320.00000000001
The 80th perc in 2013 was in category: 5
80th percentile Auck 2018: 116300.0
The 80th perc in 2018 was in category: 6
```




Therefore, the affluence indicator in the Auckland Region in 2013 is the percentage of individuals who earn an income in cat 5 and up (i.e. cat 5 + cat 6 + cat 7), whereas in 2018 it is the percentage of individuals who earn an income of cat 6 and up.

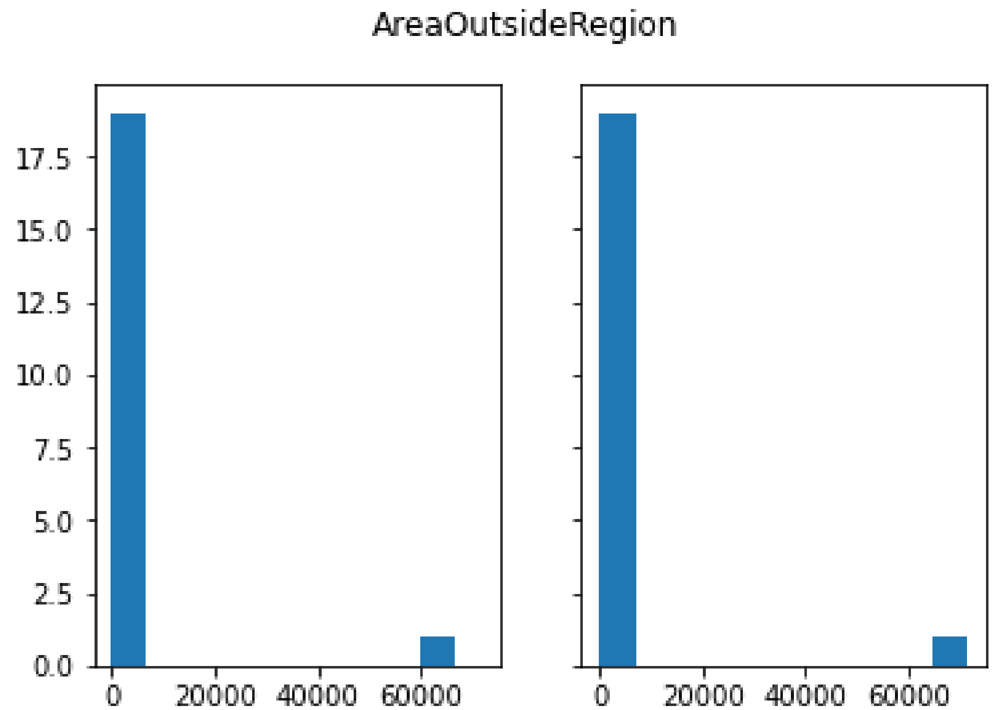
But now what about 2006? Do we just assume it's a category difference?

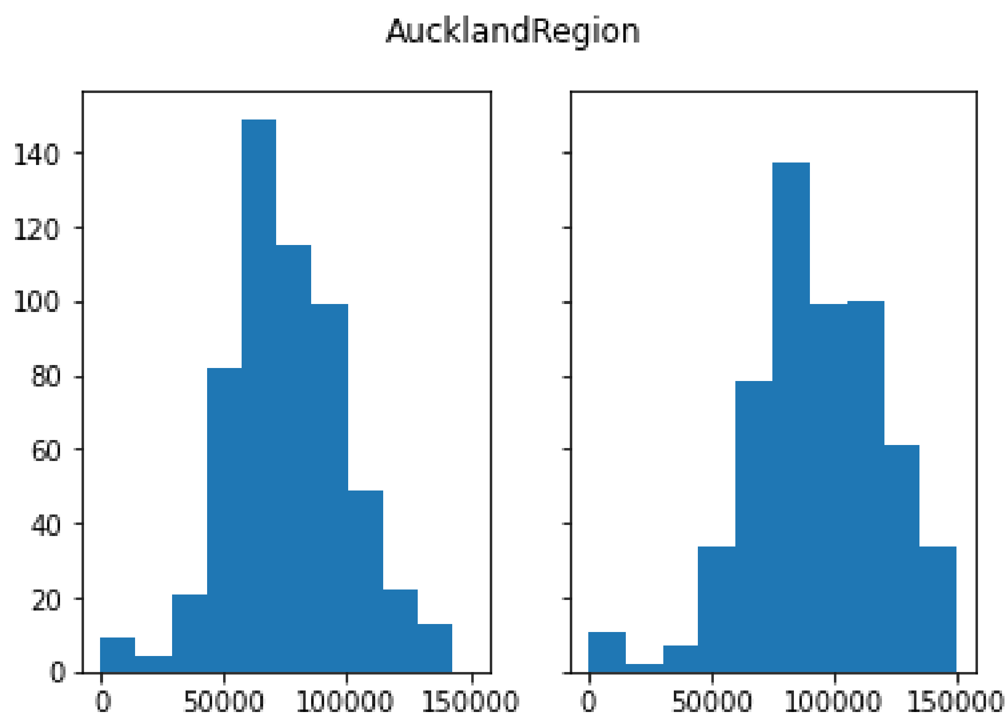
Let's test whether there are category differences in the other regions.

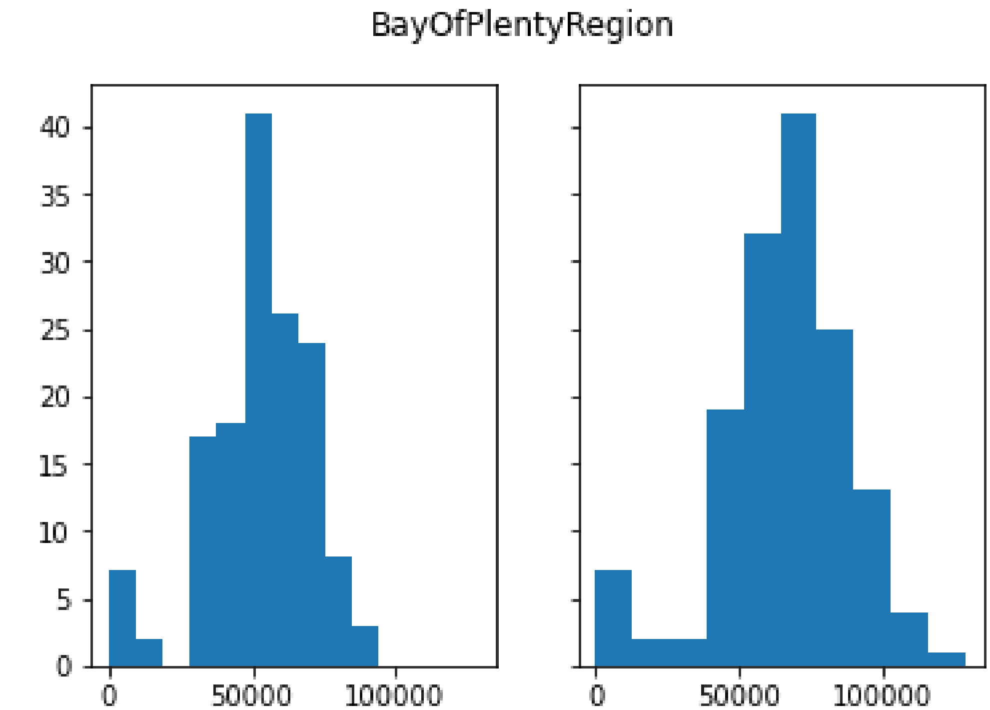
**Run for all regions and update groupD**

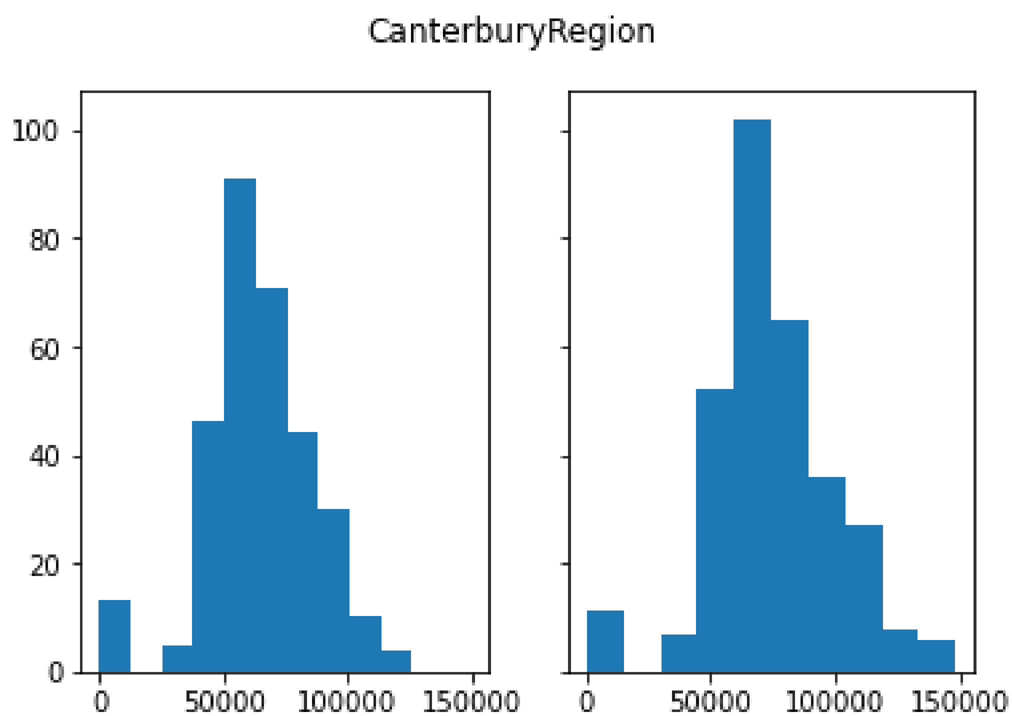
[98]:
```
def extractMed(year,region):
    medDat=np.array(groupG.loc[(groupG['Year'] == year)&(groupG['ParentArea']␣
↪== region)].MedInc.tolist())
    medDat=np.nan_to_num(medDat,copy=False,nan=0.0)
    return(medDat)

def scatters(dat2013,dat2018,region):
    fig, (ax1, ax2) = plt.subplots(1, 2,sharex=True,sharey=True)
    fig.suptitle(region)
    ax1.hist(dat2013)
    ax2.hist(dat2018)

def determinePerc(dat):
    perc=np.percentile(dat,80)
    if (perc > 50000) & (perc <= 70000):
```

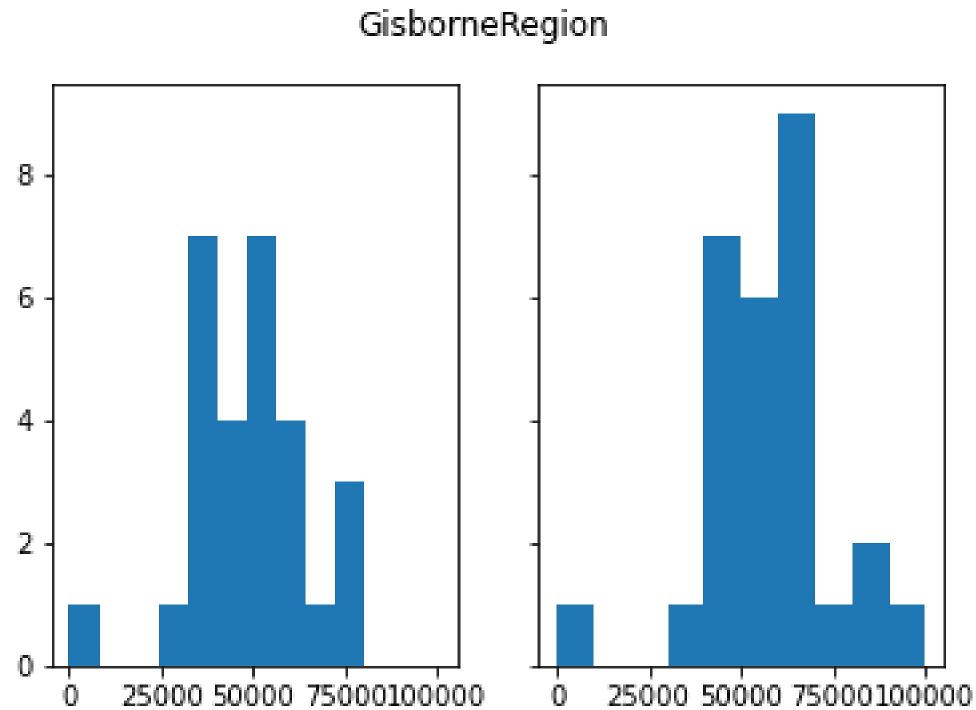
```
        cat=4
    elif (perc > 70000) & (perc <= 100000):
        cat=5
    elif (perc > 100000) & (perc <= 150000):
        cat=6
    elif (perc > 150000):
        cat=7
    else:
        cat=-99
    return(cat)

def replaceVals(year,region,cat):
    groupD.loc[(groupD['Year'] == year)&(groupD['ParentArea'] ==␣
 ↪region),'Perc_Cat']=cat


regionMaster=['AreaOutsideRegion','AucklandRegion','BayOfPlentyRegion','CanterburyRegion','Gis
            ␣
 ↪'Manawatu-WanganuiRegion','MarlboroughRegion','NelsonRegion','NorthlandRegion','OtagoRegion
             ␣
 ↪'TaranakiRegion','TasmanRegion','WaikatoRegion','WellingtonRegion','WestCoastRegion']

for region in regionMaster:
    data2013=extractMed(2013,region)
    data2018=extractMed(2018,region)
    scatters(data2013,data2018,region)
    replaceVals(2013,region,determinePerc(data2013))
    replaceVals(2018,region,determinePerc(data2018))
```

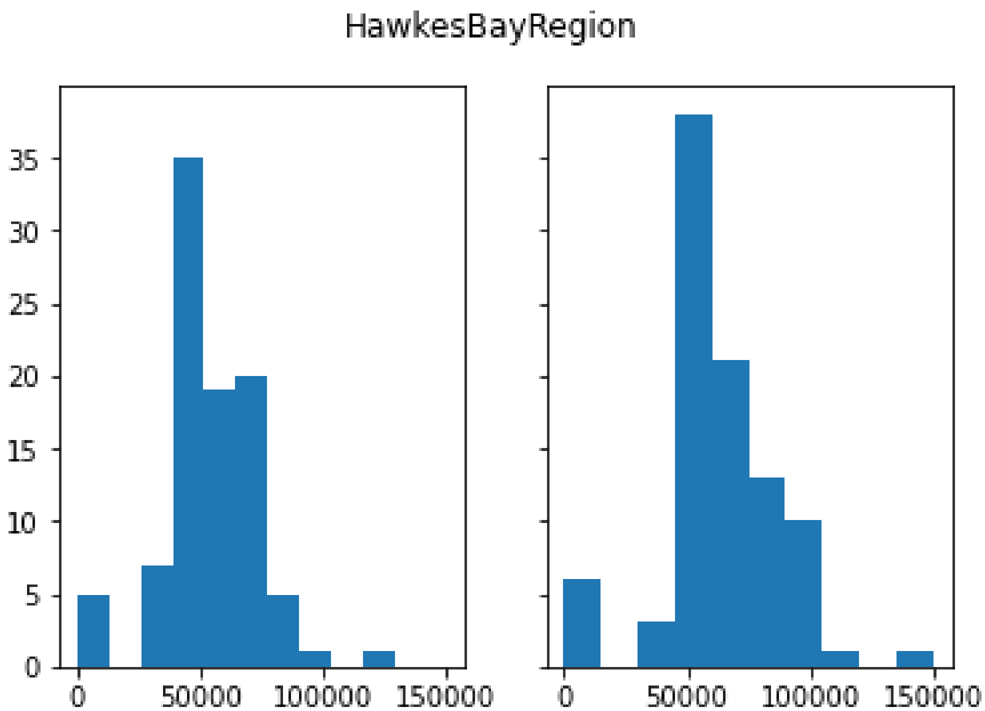

AreaOutsideRegion
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0
20000
40000
60000

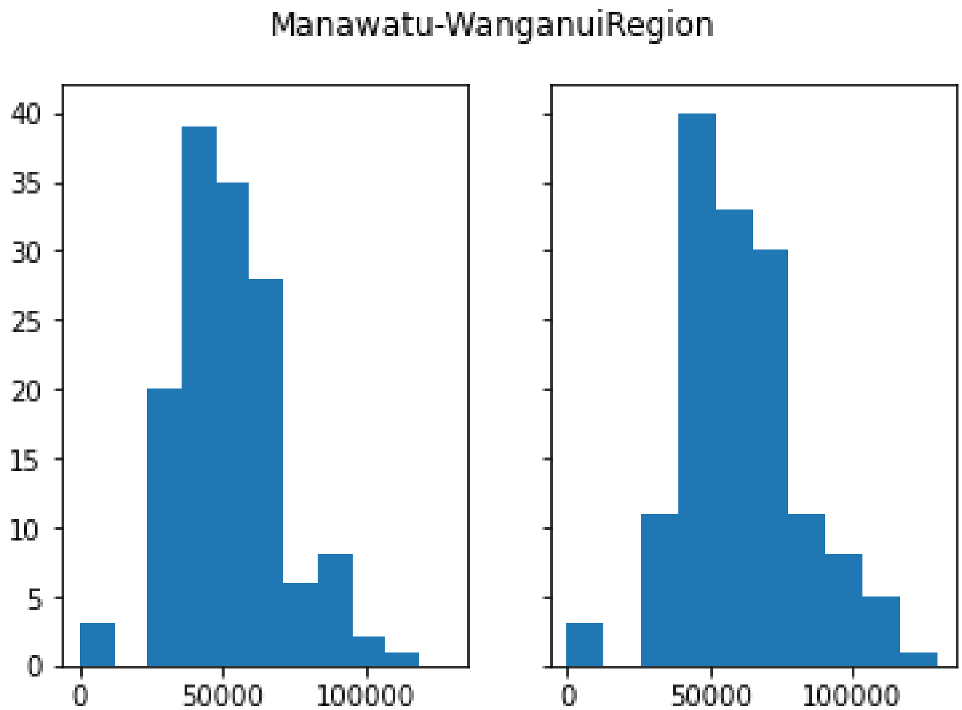

AucklandRegion
140
120
100
80
60
40
20
0
0
50000
100000
150000

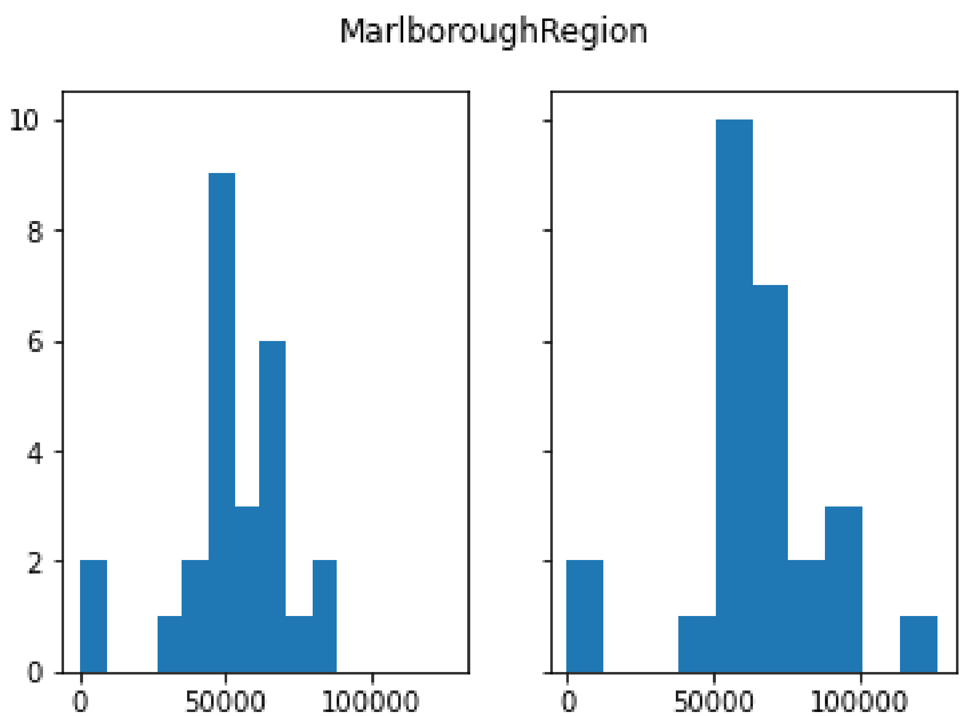

BayOfPlentyRegion
0
5
10
15
20
25
30
35
40
0
50000
100000
0
50000
100000

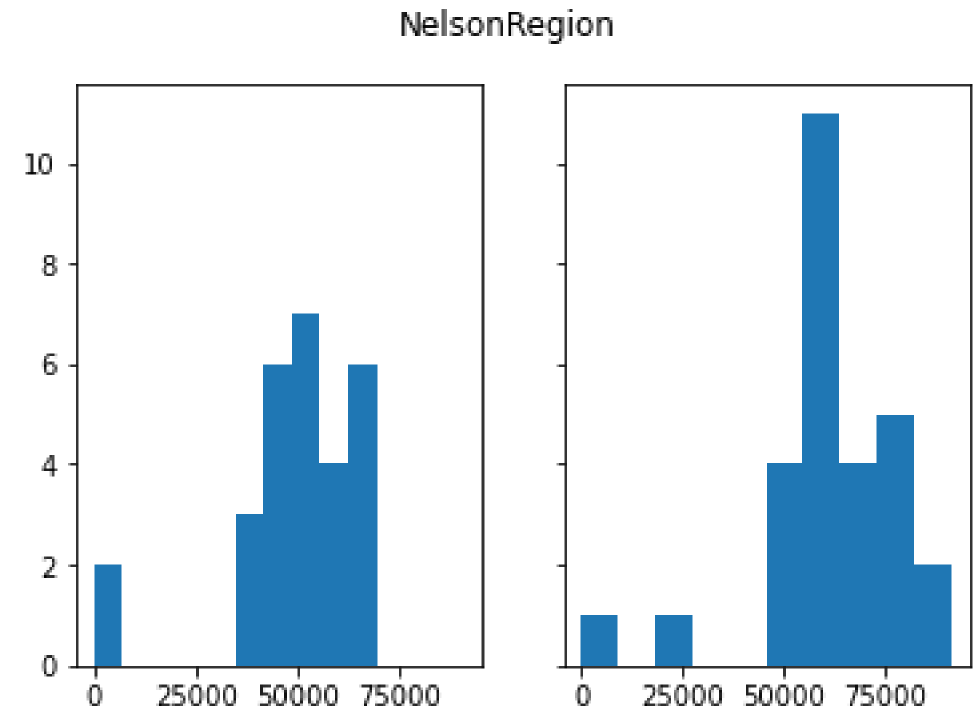

CanterburyRegion
0
20
40
60
80
100
0
50000
100000
150000
0
50000
100000
150000

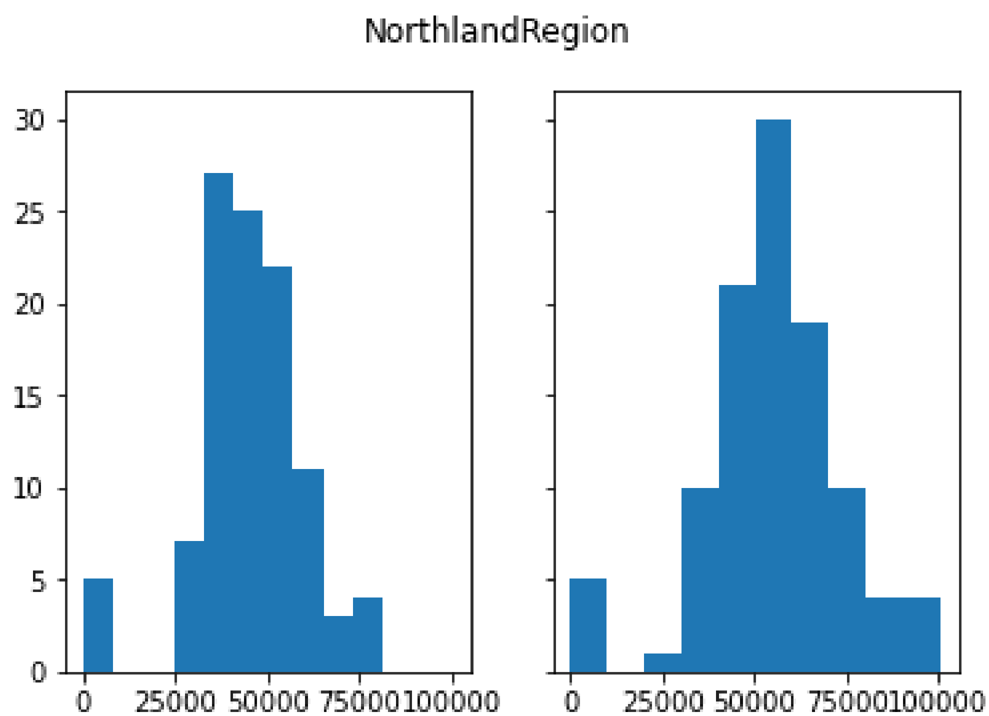

GisborneRegion
0
2
4
6
8
0
25000
50000
75000
100000

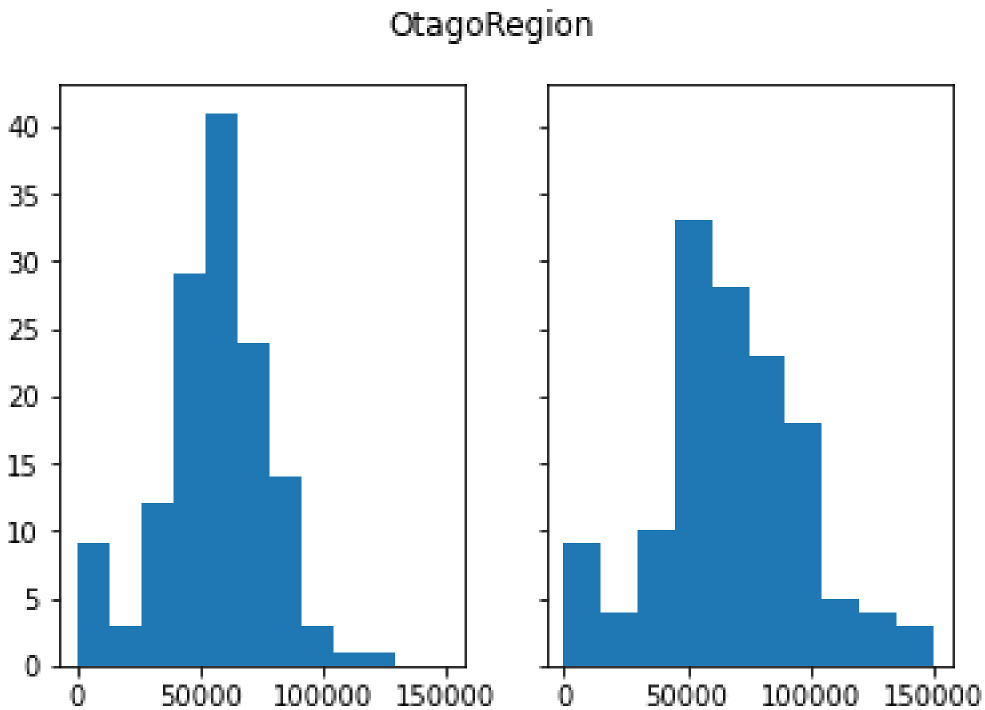

HawkesBayRegion
0
5
10
15
20
25
30
35
0
50000
100000
150000

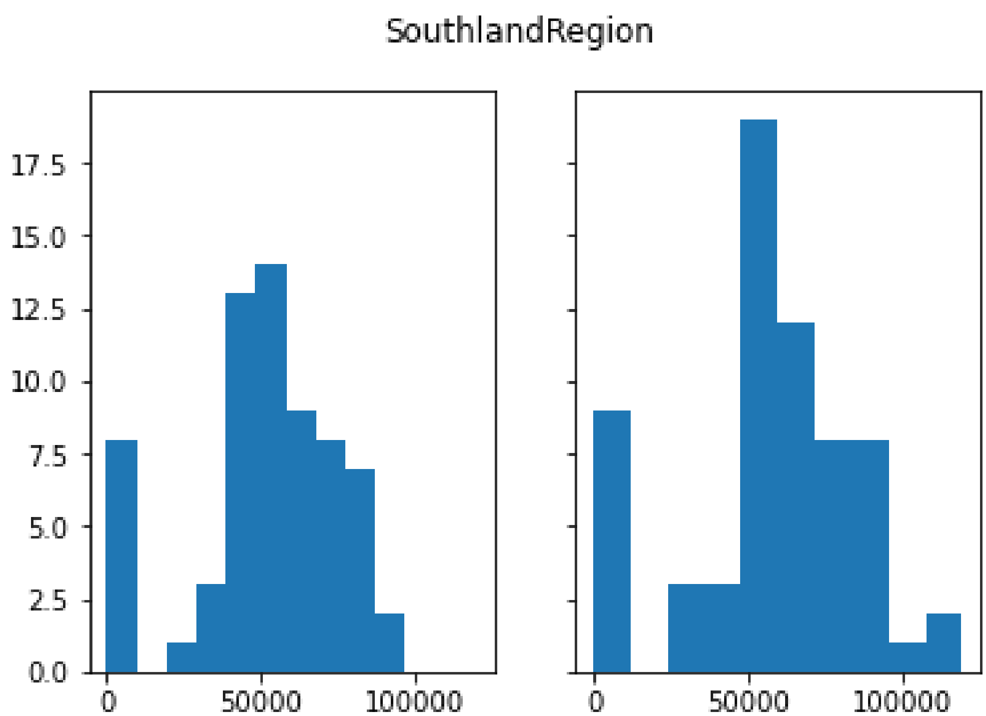

Manawatu-WanganuiRegion
0
5
10
15
20
25
30
35
40
0
50000
100000

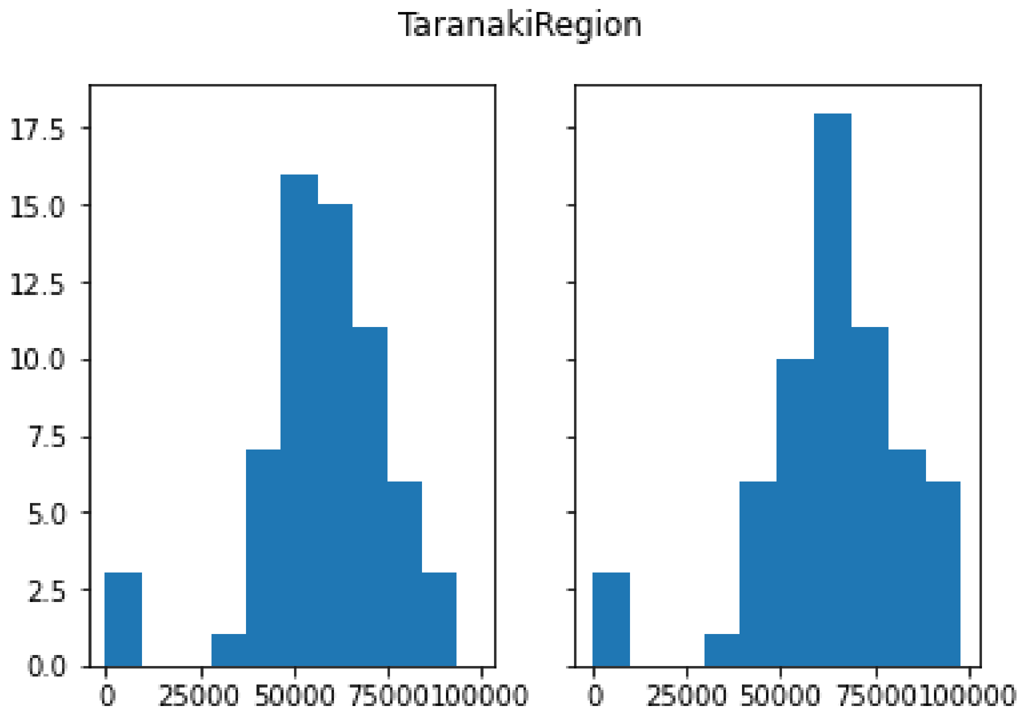

MarlboroughRegion
0
2
4
6
8
10
0
50000
100000

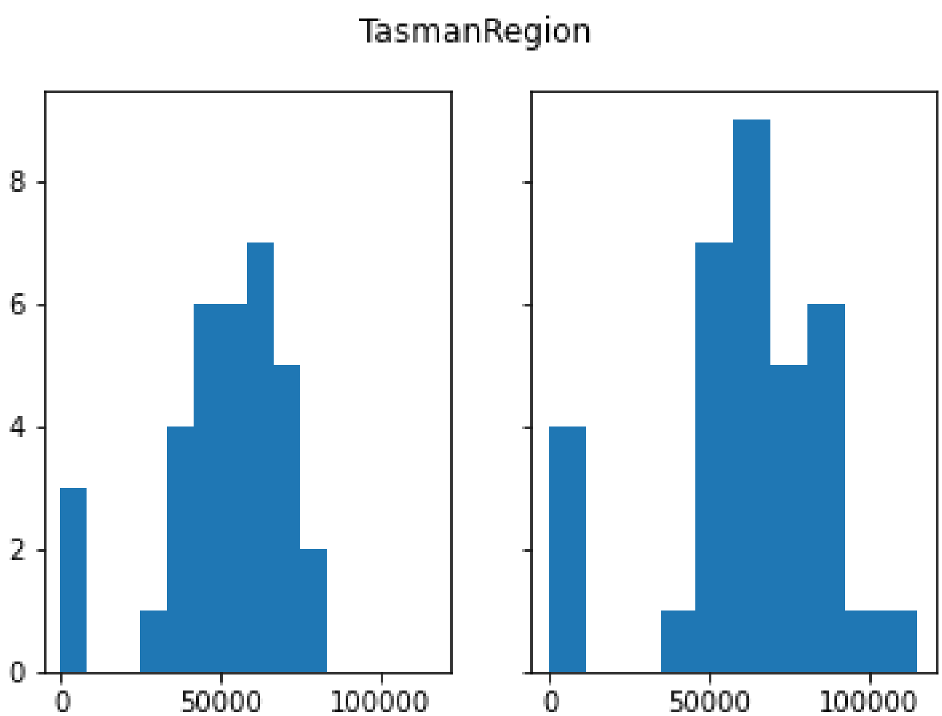

NelsonRegion
0
2
4
6
8
10
0
25000
50000
75000

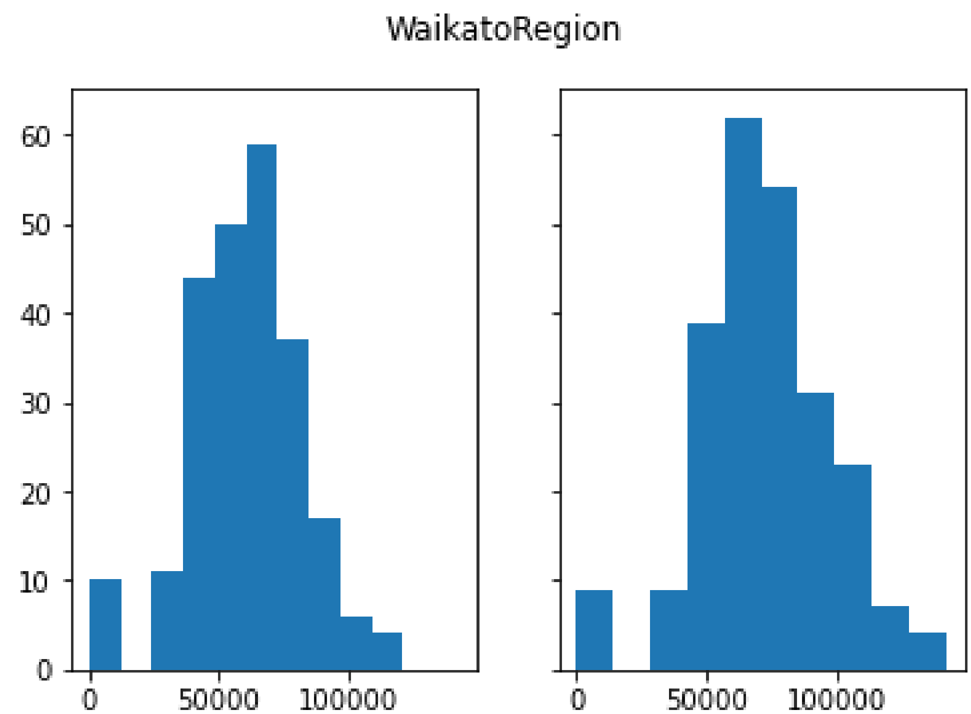

NorthlandRegion
0
5
10
15
20
25
30
0
25000
50000
75000
100000

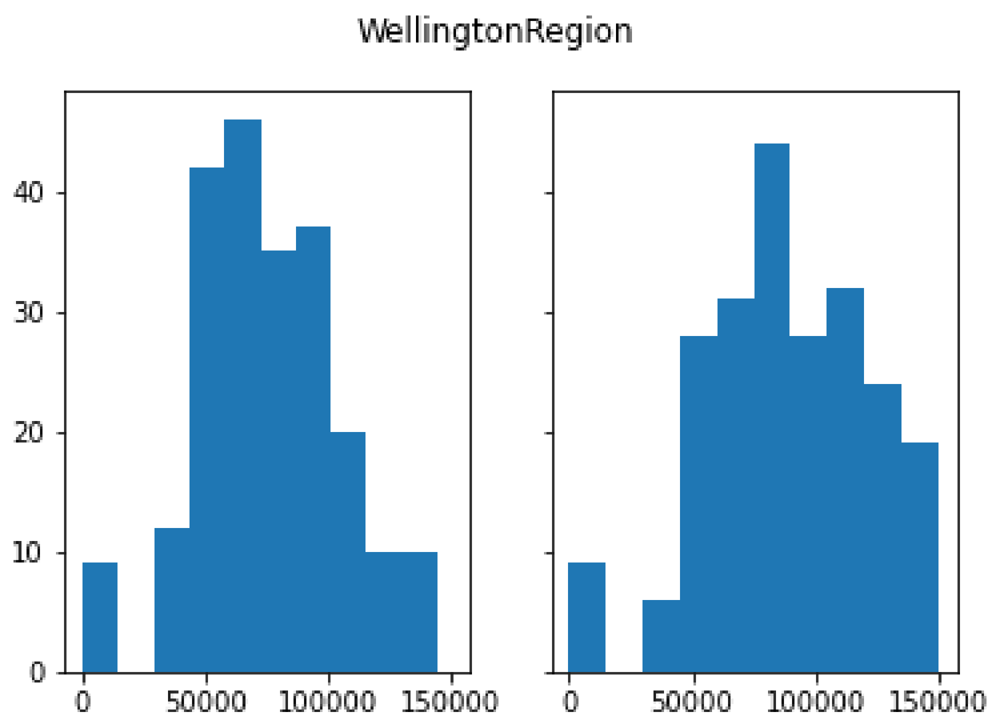

OtagoRegion
0
5
10
15
20
25
30
35
40
0
50000
100000
150000
0
50000
100000
150000

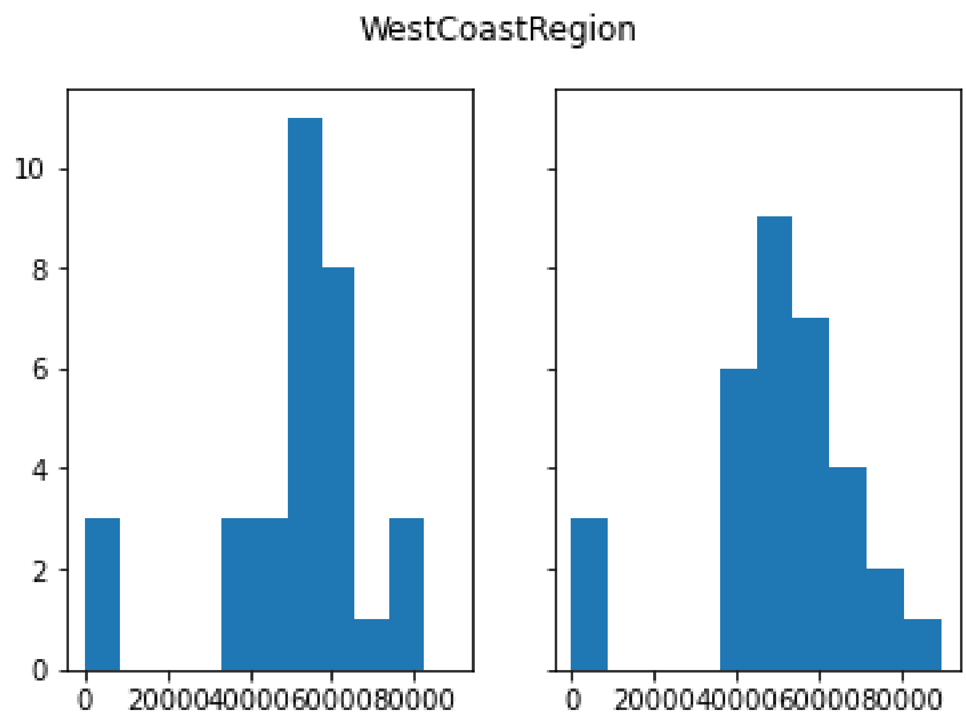

SouthlandRegion
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
0
50000
100000
0
50000
100000


TaranakiRegion
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0
25000
50000
75000
100000
0
25000
50000
75000
100000


TasmanRegion
8
6
4
2
0
0
50000
100000
0
50000
100000


WaikatoRegion
0
10
20
30
40
50
60
0
50000
100000
0
50000
100000


WellingtonRegion
0
10
20
30
40
0
50000
100000
150000
0
50000
100000
150000




[99]:
```
print("AreaOutsideRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
 ↪2013)&(groupD['ParentArea'] == 'AreaOutsideRegion')].Perc_Cat.tolist()))
print("AreaOutsideRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
 ↪2018)&(groupD['ParentArea'] == 'AreaOutsideRegion')].Perc_Cat.tolist()))
print()
print("AucklandRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
 ↪2013)&(groupD['ParentArea'] == 'AucklandRegion')].Perc_Cat.tolist()))
print("AucklandRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
 ↪2018)&(groupD['ParentArea'] == 'AucklandRegion')].Perc_Cat.tolist()))
print()
print("BayOfPlentyRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
 ↪2013)&(groupD['ParentArea'] == 'BayOfPlentyRegion')].Perc_Cat.tolist()))
print("BayOfPlentyRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
 ↪2018)&(groupD['ParentArea'] == 'BayOfPlentyRegion')].Perc_Cat.tolist()))
print()
print("CanterburyRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
 ↪2013)&(groupD['ParentArea'] == 'CanterburyRegion')].Perc_Cat.tolist()))
print("CanterburyRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
 ↪2018)&(groupD['ParentArea'] == 'CanterburyRegion')].Perc_Cat.tolist()))
print()
print("GisborneRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
 ↪2013)&(groupD['ParentArea'] == 'GisborneRegion')].Perc_Cat.tolist()))
```

```
print("GisborneRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2018)&(groupD['ParentArea'] == 'GisborneRegion')].Perc_Cat.tolist()))
print()
print("HawkesBayRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2013)&(groupD['ParentArea'] == 'HawkesBayRegion')].Perc_Cat.tolist()))
print("HawkesBayRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2018)&(groupD['ParentArea'] == 'HawkesBayRegion')].Perc_Cat.tolist()))
print()
print("Manawatu-WanganuiRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2013)&(groupD['ParentArea'] == 'Manawatu-WanganuiRegion')].Perc_Cat.tolist()))
print("Manawatu-WanganuiRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2018)&(groupD['ParentArea'] == 'Manawatu-WanganuiRegion')].Perc_Cat.tolist()))
print()
print("MarlboroughRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2013)&(groupD['ParentArea'] == 'MarlboroughRegion')].Perc_Cat.tolist()))
print("MarlboroughRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2018)&(groupD['ParentArea'] == 'MarlboroughRegion')].Perc_Cat.tolist()))
print()
print("NelsonRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2013)&(groupD['ParentArea'] == 'NelsonRegion')].Perc_Cat.tolist()))
print("NelsonRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2018)&(groupD['ParentArea'] == 'NelsonRegion')].Perc_Cat.tolist()))
print()
print("NorthlandRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2013)&(groupD['ParentArea'] == 'NorthlandRegion')].Perc_Cat.tolist()))
print("NorthlandRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2018)&(groupD['ParentArea'] == 'NorthlandRegion')].Perc_Cat.tolist()))
print()
print("OtagoRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2013)&(groupD['ParentArea'] == 'OtagoRegion')].Perc_Cat.tolist()))
print("OtagoRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2018)&(groupD['ParentArea'] == 'OtagoRegion')].Perc_Cat.tolist()))
print()
print("SouthlandRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2013)&(groupD['ParentArea'] == 'SouthlandRegion')].Perc_Cat.tolist()))
print("SouthlandRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2018)&(groupD['ParentArea'] == 'SouthlandRegion')].Perc_Cat.tolist()))
print()
print("TaranakiRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2013)&(groupD['ParentArea'] == 'TaranakiRegion')].Perc_Cat.tolist()))
print("TaranakiRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2018)&(groupD['ParentArea'] == 'TaranakiRegion')].Perc_Cat.tolist()))
print()
print("TasmanRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2013)&(groupD['ParentArea'] == 'TasmanRegion')].Perc_Cat.tolist()))
```

```
print("TasmanRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2018)&(groupD['ParentArea'] == 'TasmanRegion')].Perc_Cat.tolist()))
print()
print("WaikatoRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2013)&(groupD['ParentArea'] == 'WaikatoRegion')].Perc_Cat.tolist()))
print("WaikatoRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2018)&(groupD['ParentArea'] == 'WaikatoRegion')].Perc_Cat.tolist()))
print()
print("WellingtonRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2013)&(groupD['ParentArea'] == 'WellingtonRegion')].Perc_Cat.tolist()))
print("WellingtonRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2018)&(groupD['ParentArea'] == 'WellingtonRegion')].Perc_Cat.tolist()))
print()
print("WestCoastRegion 2013: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2013)&(groupD['ParentArea'] == 'WestCoastRegion')].Perc_Cat.tolist()))
print("WestCoastRegion 2018: ",np.unique(groupD.loc[(groupD['Year'] ==␣
↪2018)&(groupD['ParentArea'] == 'WestCoastRegion')].Perc_Cat.tolist()))
```

```
AreaOutsideRegion 2013:  [-99]
AreaOutsideRegion 2018:  [-99]

AucklandRegion 2013:  [5]
AucklandRegion 2018:  [6]

BayOfPlentyRegion 2013:  [4]
BayOfPlentyRegion 2018:  [5]

CanterburyRegion 2013:  [5]
CanterburyRegion 2018:  [5]

GisborneRegion 2013:  [4]
GisborneRegion 2018:  [4]

HawkesBayRegion 2013:  [4]
HawkesBayRegion 2018:  [5]

Manawatu-WanganuiRegion 2013:  [4]
Manawatu-WanganuiRegion 2018:  [5]

MarlboroughRegion 2013:  [4]
MarlboroughRegion 2018:  [5]

NelsonRegion 2013:  [4]
NelsonRegion 2018:  [5]

NorthlandRegion 2013:  [4]
NorthlandRegion 2018:  [4]
```

```
OtagoRegion 2013:  [5]
OtagoRegion 2018:  [5]

SouthlandRegion 2013:  [5]
SouthlandRegion 2018:  [5]

TaranakiRegion 2013:  [5]
TaranakiRegion 2018:  [5]

TasmanRegion 2013:  [4]
TasmanRegion 2018:  [5]

WaikatoRegion 2013:  [5]
WaikatoRegion 2018:  [5]

WellingtonRegion 2013:  [5]
WellingtonRegion 2018:  [6]

WestCoastRegion 2013:  [4]
WestCoastRegion 2018:  [4]
```

How do we know whether we can extrapolate the trend back to 2006? Consider regional GDP growth 2006-2013-2018

I drew the stats for regional GDP (RNA) per person from StatsNZ and compared the growth rates between 2006-2013 and 2013-2018. There is NO OBVIOUS LOGICAL CONNECTION between the nominal annual growth rates and whether a egion's 80th percential median income jumped a category or not.

This may be because the categories are too broad. What if I compare growth in RNA to growth in 80th percentile of median income?

**Calculating growth rates in 80th percentile of median income**

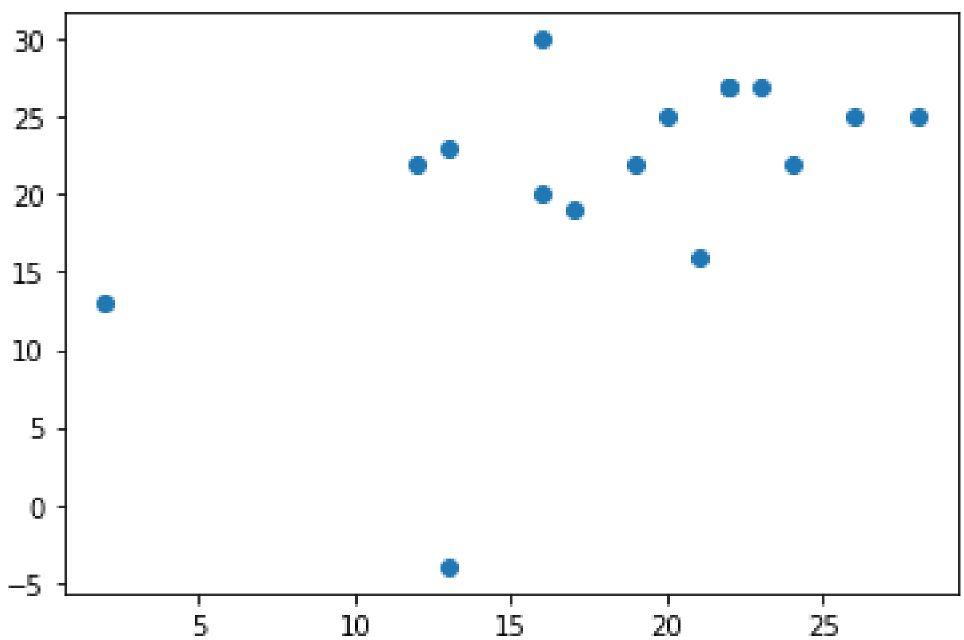
[80]:
```
#RNA growth rates from excel sheet
arr2=np.array([27,27,19,23,22,20,30,25,27,25,22,-4,25,22,16,13])
arr1 = np. array([])
for region in regionMaster:
    data2013=extractMed(2013,region)
    data2018=extractMed(2018,region)
    perc2013=np.percentile(data2013,80)
    perc2018=np.percentile(data2018,80)
    if perc2018-perc2013!=0:
        arr1=np.append(arr1,round((perc2018-perc2013)/perc2013*100))
        print("Growth for ",region,":",round((perc2018-perc2013)/
 ↪perc2013*100),"%")
```

```
Growth for  AucklandRegion : 22 %
```

```
Growth for  BayOfPlentyRegion : 23 %
Growth for  CanterburyRegion : 17 %
Growth for  GisborneRegion : 13 %
Growth for  HawkesBayRegion : 24 %
Growth for  Manawatu-WanganuiRegion : 16 %
Growth for  MarlboroughRegion : 16 %
Growth for  NelsonRegion : 20 %
Growth for  NorthlandRegion : 22 %
Growth for  OtagoRegion : 28 %
Growth for  SouthlandRegion : 12 %
Growth for  TaranakiRegion : 13 %
Growth for  TasmanRegion : 26 %
Growth for  WaikatoRegion : 19 %
Growth for  WellingtonRegion : 21 %
Growth for  WestCoastRegion : 2 %
```

[82]:
```
plt.scatter(arr1, arr2)
```

[82]:
```
<matplotlib.collections.PathCollection at 0x1256f4670>
```




Nope… nothing there either.

OK. So in lieu of a better understanding on what drove the change in median household incomes, I choose to leave the category for 2006 the same as it was for 2013. This is a conservative approach as you would have had to be MORE affluent in 2006 to make it into the affluence category.

### 1.0.3 Add the 2013 category to 2006

[102]:
```
for region in regionMaster:
    cat=np.unique(groupD.loc[(groupD['Year'] == 2013)&(groupD['ParentArea'] ==␣
 ↪region),'Perc_Cat'])
    groupD.loc[(groupD['Year'] == 2006)&(groupD['ParentArea'] ==␣
 ↪region),'Perc_Cat']=cat[0]

groupD.to_csv("groupD_catMatch.csv")
```