# **Data pre-processing**

3 datasets: crime dataset, cost of living dataset, unemployment dataset.



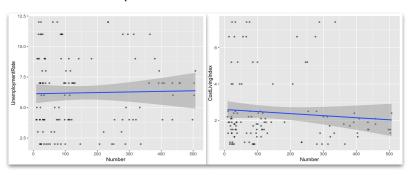
- Clean and structured
- Result

^	District <sup>‡</sup>	Time ‡	Type	Number <sup>‡</sup>	UnemploymentRate <sup>‡</sup>	CostLivingIndex <sup>‡</sup>
1	Canterbury	2017Q3	Unlawful Entry With Intent/Burglary, Break and Enter	37	4.6	1.9
2	Canterbury	2017Q4	Unlawful Entry With Intent/Burglary, Break and Enter	101	4.4	1.8
3	Canterbury	2018Q1	Unlawful Entry With Intent/Burglary, Break and Enter	111	4.6	1.7
4	Canterbury	2018Q2	Unlawful Entry With Intent/Burglary, Break and Enter	126	4.4	1.9
5	Canterbury	2018Q3	Unlawful Entry With Intent/Burglary, Break and Enter	73	3.9	2.2
6	Canterbury	2018Q4	Unlawful Entry With Intent/Burglary, Break and Enter	124	4.4	2.1
7	Canterbury	2019Q1	Unlawful Entry With Intent/Burglary, Break and Enter	130	4.4	1.3
8	Canterbury	2019Q2	Unlawful Entry With Intent/Burglary, Break and Enter	114	3.9	1.5

## Data Analysis: Pearson's correlation coefficient analysis

#### Five conditions

- Condition 1: continuous variables
- Condition 2: The continuous variables should be paired
- Condition 3: There is a linear relationship

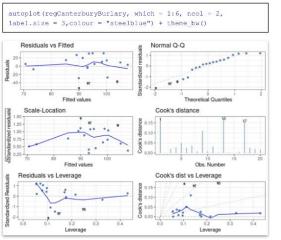


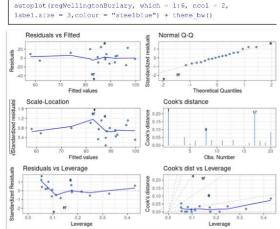
### Condition 4: no obvious outliers

```
> summary(Crime_Offenders$Number)
   Min. 1st Ou. Median
                          Mean 3rd Ou.
                                           Max.
                90.00 149.83 259.50 507.00
> summary(Crime_Offenders$UnemploymentRate)
   Min. 1st Qu. Median
                           Mean 3rd Ou.
                                           Max.
                                         12.00
                           6.20
> summary(Crime_Offenders$CostLivingIndex)
   Min. 1st Qu. Median
                           Mean 3rd Ou.
                                          Max.
  0.700
         1.300
                 1.850
                          2.430
                                 2.425
                                         7.400
```

```
> is.na(Crime_Offenders$Number)
       [17] FALSE FALSE
                               FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE 
       [49] FALSE FALSE
       [65] FALSE FALSE
       T817 FALSE FALSE
                               FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE 
 [113] FALSE FALSE FALSE FALSE FALSE FALSE FALSE
 > is.na(Crime_Offenders$UnemploymentRate)
       [1] FALSE FA
       TITI FALSE FALSE
       733 FALSE FALSE
       7497 FALSE FALSE
       [65] FALSE FALSE
       [81] FALSE FALSE
       [97] FALSE FALSE
[113] FALSE FALSE FALSE FALSE FALSE FALSE FALSE
 > is.ng(Crime_Offenders$CostLivingIndex)
       [1] FALSE FA
       [17] FALSE FALSE
       733 FALSE FALSE
       [49] FALSE FALSE
       [65] FALSE FALSE
       T817 FALSE FALSE
     [97] FALSE F
 [113] FALSE FALSE FALSE FALSE FALSE FALSE FALSE
```

### Condition 5: normal distribution





shapiro.test(Crime\_Offenders\$Number)
shapiro.test(Crime\_Offenders\$UnemploymentRate)
shapiro.test(Crime\_Offenders\$CostLivingIndex)

Q–Q plot

Shapiro-Wilk test function

### Data Analysis: Pearson's correlation coefficient analysis

```
> cor.test(Crime_Offenders$Number,Crime_Offenders$UnemploymentRate)
        Pearson's product-moment correlation
data: Crime_Offenders$Number and Crime_Offenders$UnemploymentRate
t = 0.25008, df = 118, p-value = 0.803
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
-0.1568725 0.2014264
sample estimates:
       cor
0.02301603
> cor.test(Crime_Offenders$Number,Crime_Offenders$CostLivingIndex)
        Pearson's product-moment correlation
data: Crime_Offenders$Number and Crime_Offenders$CostLivingIndex
t = -0.97043, df = 118, p-value = 0.3338
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
-0.26401132 0.09172354
sample estimates:
       cor
-0.0889807
```

- Cor
  - 0.0230
  - 0.0889

0</r/<0.2

- P-value
  - 0.803
  - 0.338

>0.05

Very weak correlation or no correlation!

# **Data Analysis**: Linear Regression analysis

```
> regCanterburyBurlary<-lm(formula=Crime_Offenders_Canterbury_Burglary$Number~Crime_Offenders_Canterbury_B
urglary$CostLivingIndex +Crime_Offenders_Canterbury_Burglary$UnemploymentRate)
> summary(regCanterburyBurlary)
Call:
lm(formula = Crime_Offenders_Canterbury_Burglary$Number ~ Crime_Offenders_Canterbury_Burglary$CostLivingIn
dex +
   Crime_Offenders_Canterbury_Burglary$UnemploymentRate)
                                                                  statistically
Residuals:
   Min
            10 Median
                                  Max
                                                                  non-significant!
-53.027 -12.477   5.361   15.931   31.047
Coefficients:
                                                   Estimate Std. Error t value Pr(>|t|)
                                                               26.097 4.785 0.000172 ***
(Intercept)
                                                    124.867
Crime_Offenders_Canterbury_Burglary$CostLivingIndex
                                                    -6.660
                                                                4.441 -1.500 0.152044
Crime_Offenders_Canterbury_Burglary$UnemploymentRate -2.465
                                                                2.702 -0.912 0.374428
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' '1
Residual standard error: 26.76 on 17 degrees of freedom
Multiple R-squared: 0.118,
                              Adjusted R-squared 0.01425
F-statistic: 1.137 on 2 and 17 DF,
                                 p-value: 0.3439
```