## ANALYSIS OF NYC SERVICE REQUEST CALLS TO 311

### **Outline**

- Data ETL
- MVA
  - CA, PCA, MCA
  - Clustering, Tree classification
- Conclusions

### Data from:

- NYC OpenData
- NYPD DB
- IRS
- US Census Office

All material and code available at:

https://www.github.com/Cbhihe/nyc311



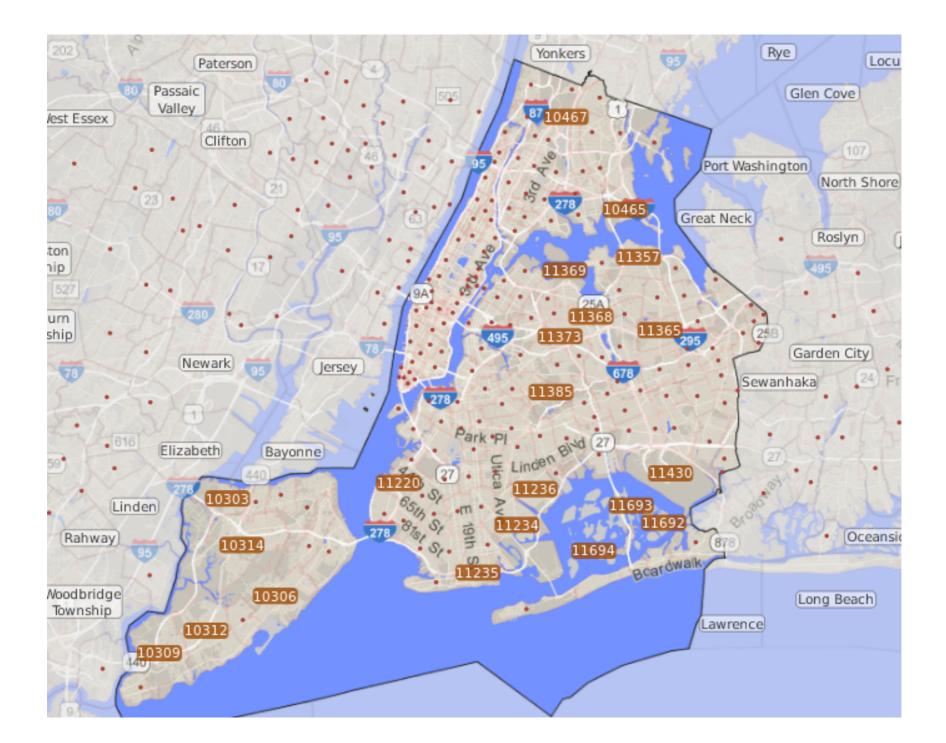


### 5 boroughs:

- ⇒ > 200 ZIPs
- ⇒ 8.7 M. people
- ⇒ 100,000 SRC to 311 /month

## Objective(s):

- to explore data with MVA tools
- to extract features and descriptive information, so we may:
  - detect trends
  - optimize urban resources



Data ETL – extract



### Data ETL – reduce

Period¶	Raw-data's obs-number¶		Obs·#·missing·all location·info¶	Service requests' modalities #¶	Unique¶ ZIP¶
April·2014¶	81645¶	3206¶	2740¶	170¶	278¶
April·2015¶	101890¶	4231¶	3069¶	178¶	260¶

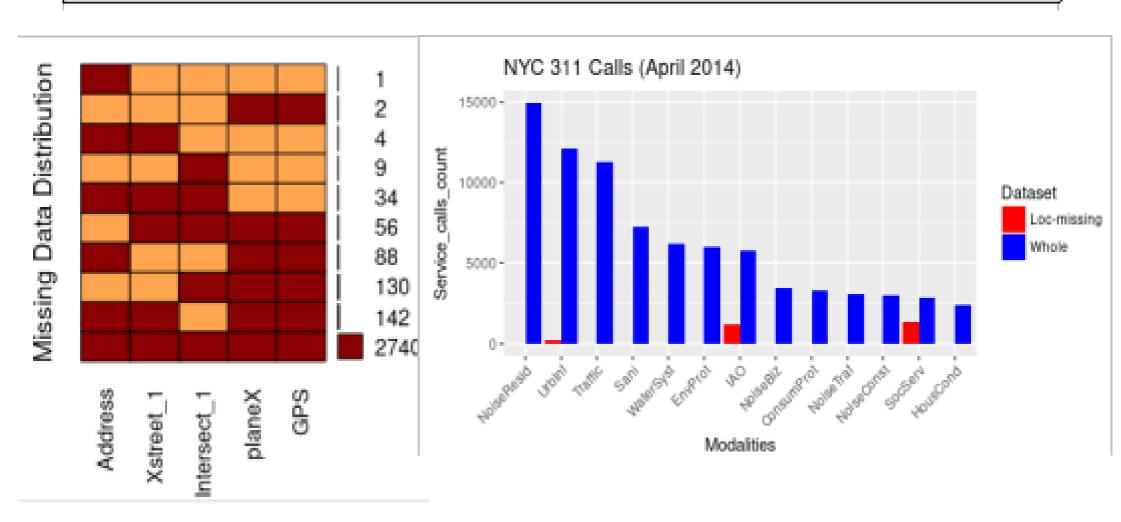
- Between 150 and 200 different SRCs' raw features
- Reduce to 13 features by consolidating calls' objects

## <u>Data ETL</u> <u>– reduce</u>

Service request	Modality-description¶	Service re freque	Change in rank from	
cans modanties <sub>1</sub>		April·2014¶	April·2015¶	2014-to-2015¶
NoiseResid¶	Residential Noise	19.00%9	17.50%9	-¶
UrbInf¶	Urban In frastructure	15.00%9	13.40%9	<b>⊁</b> ¶
Traffic¶	Traffic related Issues¶	14.30%9	17.20%9	<b>*</b> ¶
Sani¶	Unsanitary-Conditions¶	9.20%	10.50%9	<b>-</b> ¶
WaterSyst¶	Water-Systems¶	7.80%9	7.60%9	<b>-</b> ¶
EnvProt¶	Environmental Protection¶	7.60%9	5.90%9	<b>-</b> ¶
POAL	Inspect, Audit, Order¶	5.80%9	5.20%9	¥¶
NoiseBiz¶	Commercial Noise¶	4.40%9	4.90%9	×¶
ConsumProt¶	Comsumer Protection¶	4.20%	3.40%9	¥¶
NoiseTraf¶	Traffic Noise¶	3.90%	5.40%9	7.7¶
NoiseConst¶	Construction Noise¶	3.80%9	3.70%9	<b>1</b> ¶
HousCond¶	Housing Conditions ¶	3.10%9	3.40%9	-¶
SocServ¶	Social-Services¶	1.90%	1.90%9	<b>-</b> ¶
	Total number of SRCs	788259	986499	**¶

### **Data ETL – impute missings**

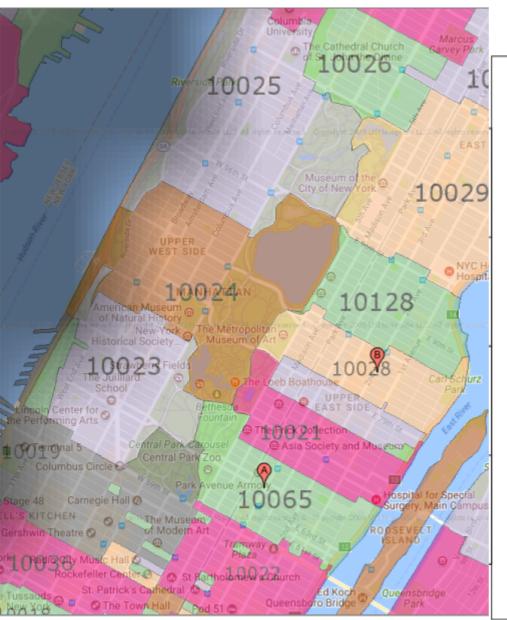
Period¶	Raw-data's obs-number¶	Obs # with missing ZIP¶	Obs·#·missing·all location·info¶	Service requests' modalities #¶	Unique¶ ZIP¶
April·2014¶	81645¶	3206¶	2740¶	170¶	278¶



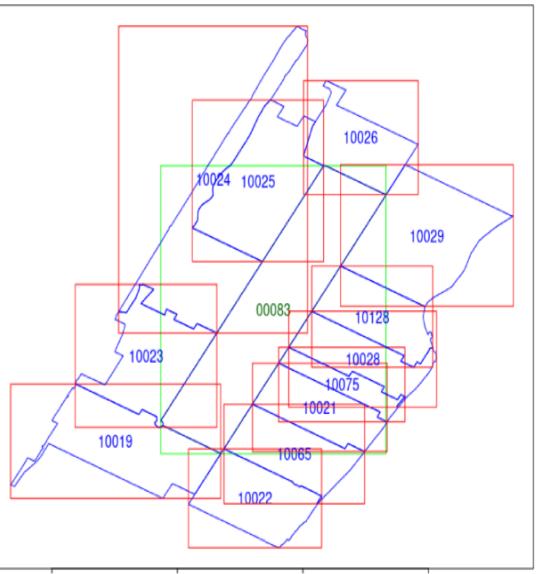
### Data ETL - clean



### Data ETL - clean



#### NYC ZIP codes neighboring with "00083"



## Data ETL – impute / clean

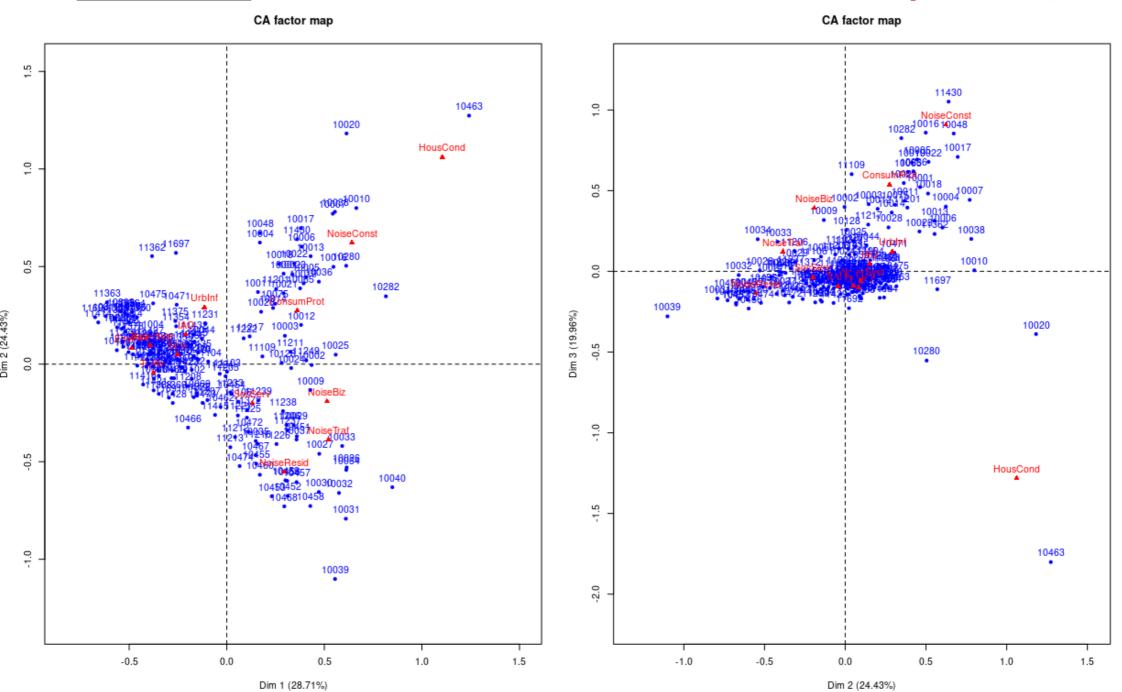


(April 2014)

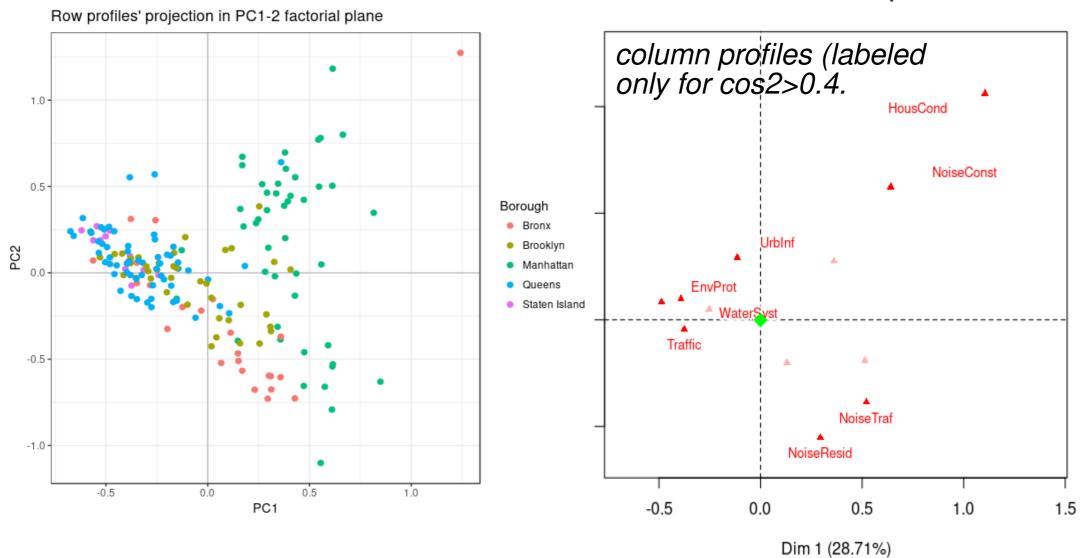
- Build frequency table (row profiles for ZIPs, column profiles for SRCs)
- Observe how 26 row marginals < 5 / nbr\_calls</li>
  - $\rightarrow$  Can we suppress them ? (...  $\chi^2$ -test of independence)
- Run CA with row marginals as row profile weights ( χ²-metric)

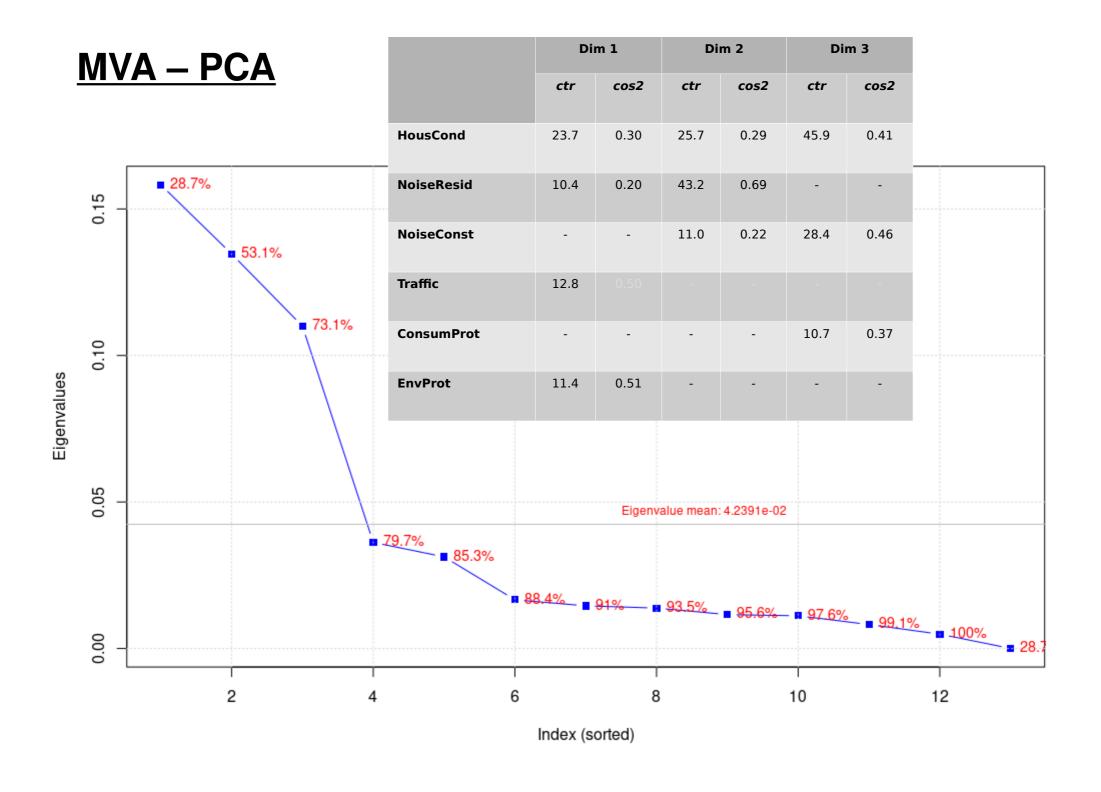
MVA - CA

(April 2014)

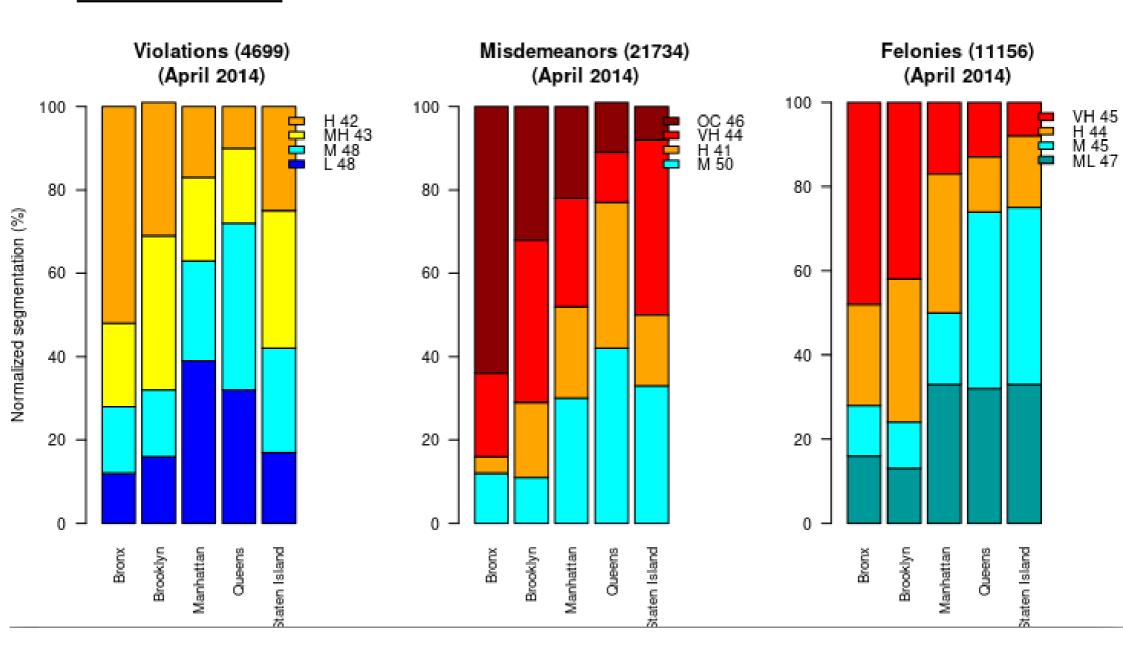


### **CA factor map**

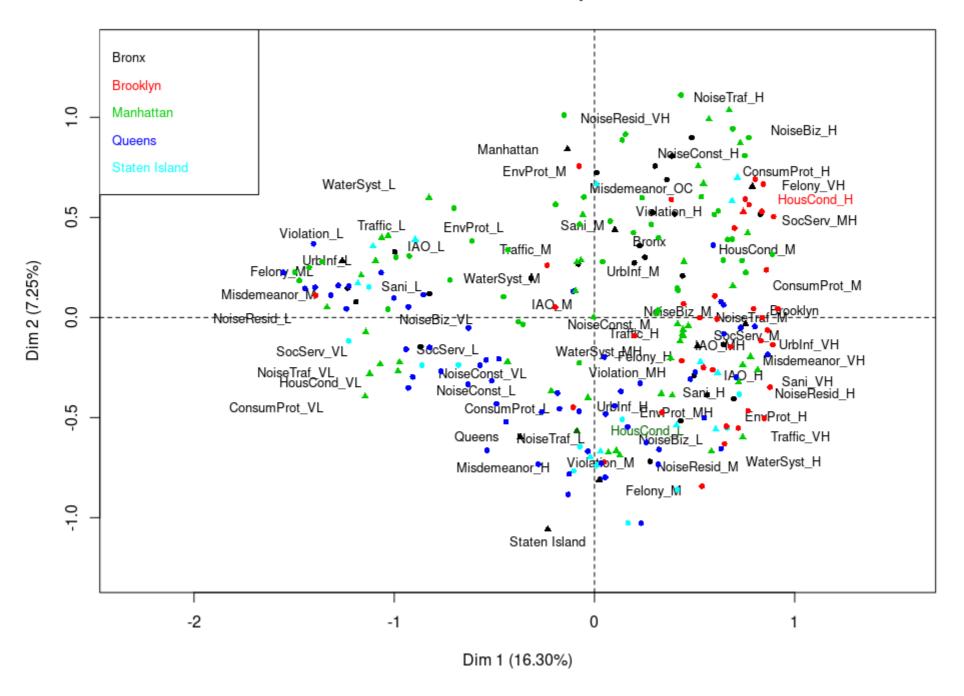


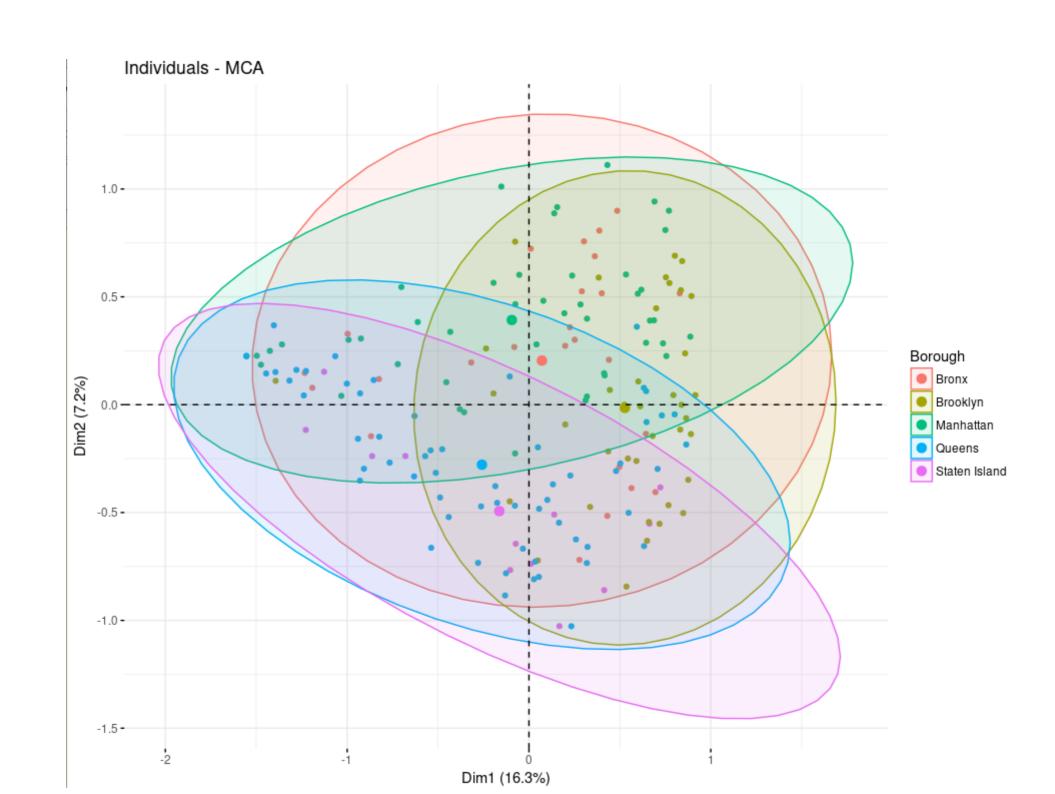


### MVA - MCA



#### MCA factor map





- In this section we present an attempt to clusterize our data set.
- This attempt is carried out by applying, in the following order:
  - Probabilistic clustering with k-means replications
  - Hierarchical clustering
  - Clustering consolidation using k-means.

• Selection of the optimal number of clusters:

#### Selection of optimal number of clusters (by k-means)

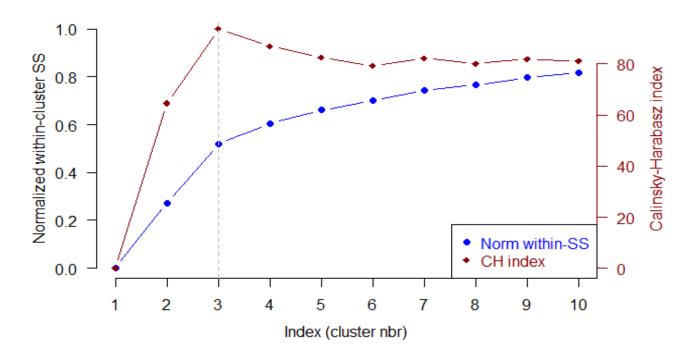
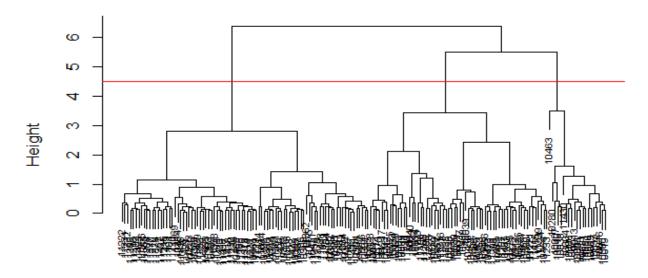


Figure 13. Selection of optimal number of clusters

• Selection of the optimal number of clusters:

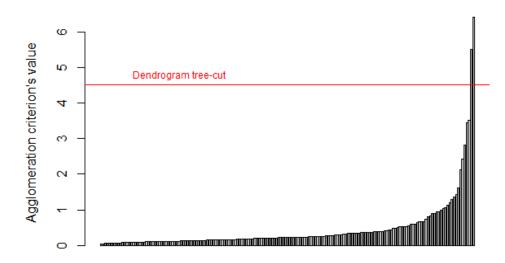
#### Hierarchical Clustering (Ward.D2)



Distance hclust (\*, "ward.D2")

• Selection of the optimal number of clusters:

#### **Clustering heights**

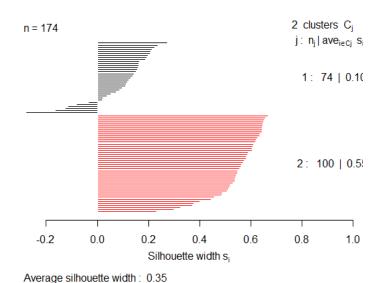


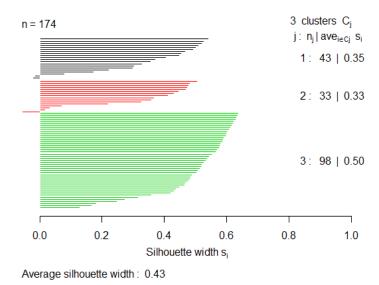
Agglomeration index

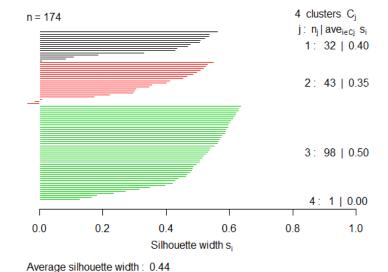
	G1	G2	G3
PC1	0,44	0,23	-0,36
PC2	0,58	-0,28	0,08
PC3	0,35	0,00	-0,06
PC4	-0,18	-0,02	0,01
PC5	-0,08	0,02	0,03

**Table 7**. Centroids of the clusters

### • Silhouette method:

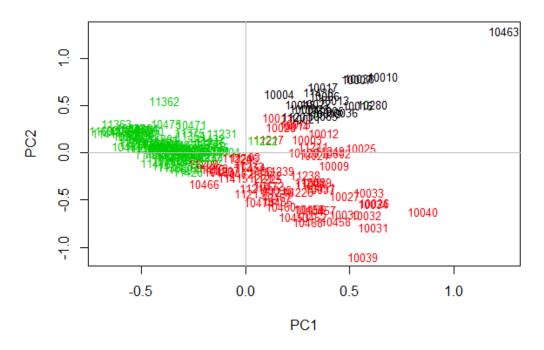




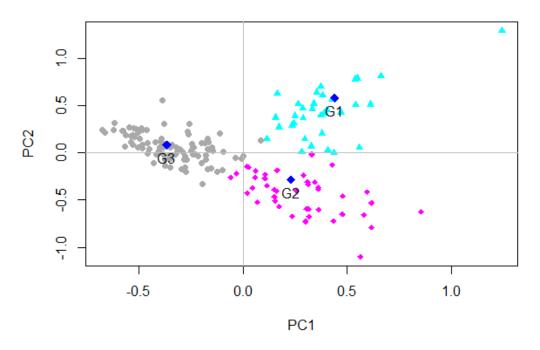


• Visualize partitions:

#### Clustering of observations in 3 classes

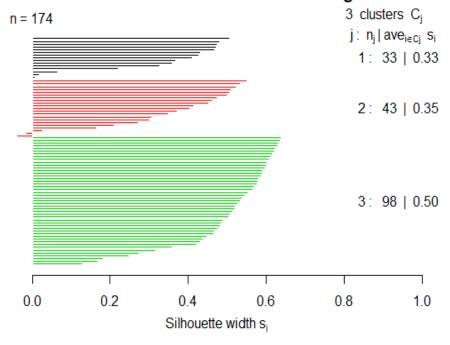


#### Consolidated clustering of observations in 3 classes



• Silhouette method after consolidation:

#### Silhouette widths for consolidated clustering



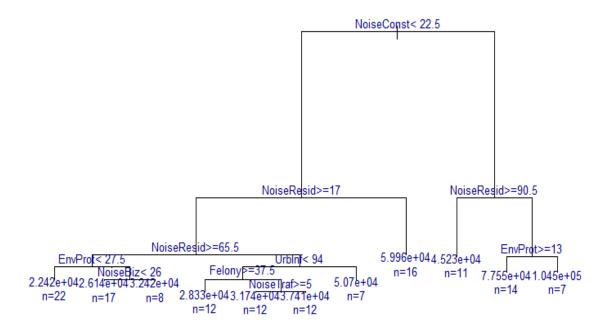
Average silhouette width: 0.43

- Categorical description to interpret the clusters:
  - We reject the null hypothesis at the risk 0.05 of being wrong when the p-values <0.05.
  - Variables for which we reject H0 -> meaningful categorization:

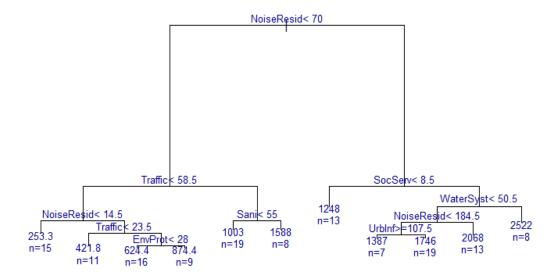
Cat1	v.test	Mean in category	Overall mean	sd in category	Overall sd	p.value
NoiseConst	9,145613	59,242424	17,132184	44,958587	29,298499	5,93E-20
ConsumProt	8,694289	43,303030	18,385057	25,590582	18,236820	3,49E-18
UrbInf	4,484378	98,575758	67,804598	55,909575	43,662851	7,31268E-06
NoiseBiz	3,328495	33,787879	19,885057	29,805183	26,578197	0,000873166
HousCond	3,277523	39,090909	13,856322	108,106391	48,991520	0,001047222
NoiseTraf	2,004039	23,393939	17,465517	17,769465	18,823636	0,045065931
Sani	-1,960935	32,939394	41,557471	25,178080	27,965180	0,049886588
NoiseResid	-2,335256	58,606061	85,896552	48,646492	74,361347	0,019530032
WaterSyst	-2,425274	26,696970	35,454023	16,983923	22,975641	0,015296833
EnvProt	-3,539835	18,424242	34,379310	13,407439	28,680460	0,000400377
Traffic	-4,138211	33,757576	64,637931	21,908944	47,483221	3,50025E-05

- In first place, we build the 2 possible decision trees:
  - One related to each of the 2 decision variables that we have ("medianInc" and "jlBenef").
- Before building the trees we split the dataset in training (80% of individuals) and test (20% of individuals).

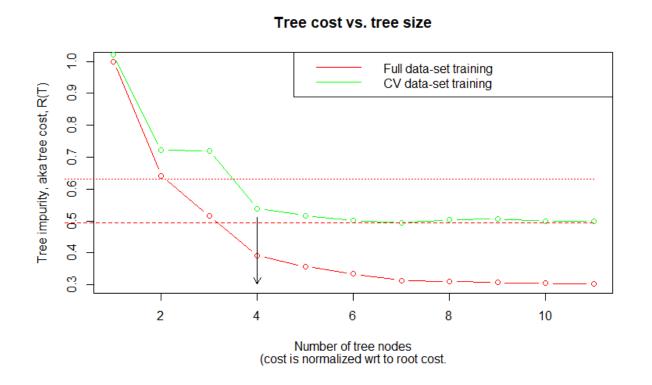
Fully grown decision tree for training data-set and "medianInc" as decision variable.



Fully grown decision tree for training data-set and "jlBenef" as decision variable.

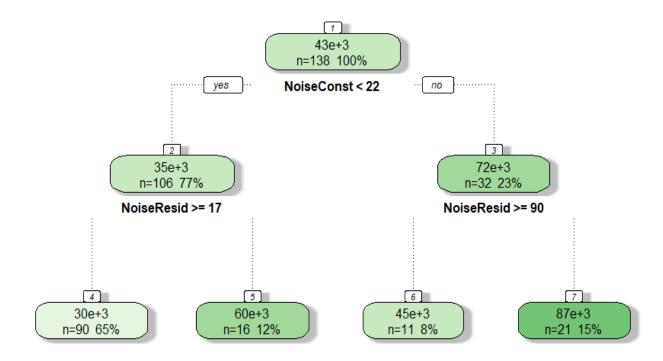


• CV normalized error mean and the whole data set based training error as a function of tree size:



- Red horizontal dashed line (below) -> minimum tree impurity (MTI) level
- Red dotted line (above) ->
   MTI + 1.
- Black arrow -> optimum number of nodes for postpruning.

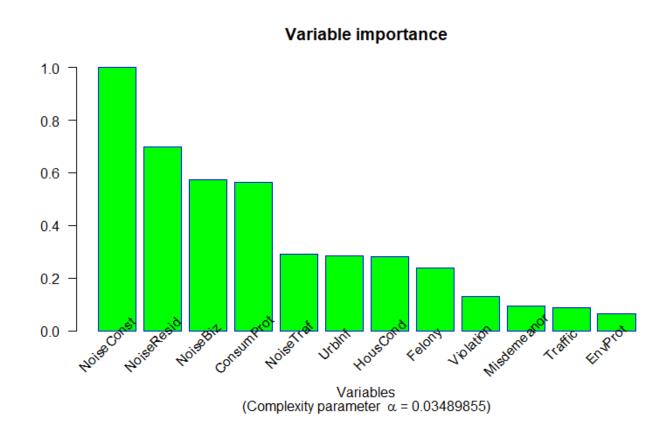
- Post-pruning:
  - Optimum complexity parameter ->  $\alpha$ opt = 0.03489.
  - Now, we are able to post-prune the decision tree by using ->  $\alpha$ opt.



- Post-pruning:
  - Split rules:

```
Rule number: 4 [medianInc=30240.922222222 cover=90 (65%)]
 NoiseConst< 22.5
 NoiseResid>=17
Rule number: 7 [medianInc=86539.2380952381 cover=21 (15%)]
 NoiseConst>=22.5
 NoiseResid < 90.5
Rule number: 5 [medianInc=59963.4375 cover=16 (12%)]
 NoiseConst< 22.5
 NoiseResid < 17
Rule number: 6 [medianInc=45225.8181818182 cover=11 (8%)]
 NoiseConst>=22.5
 NoiseResid>=90.5
```

• Variable Importance for the optimally pruned decision tree :



• Predictions:

 Slice of the original results-table which contains the predictions for each value of "medianInc" in the test data set.

	4 predicted classes				
"medianInc " for Test- set	30240,9222	45225,8182	59963,4375	86539,2381	
17992	1	0	0	0	
18164	1	0	0	0	
26143	1	0	0	0	
26170	1	0	0	0	
27102	1	0	0	0	
27144	1	0	0	0	
27203	1	0	0	0	
27303	1	0	0	0	
27331	1	0	0	0	
27374	1	0	0	0	
27898	1	0	0	0	
90981	1	0	0	0	
92955	0	0	0	1	
93056	0	0	1	0	
95992	0	0	0	1	
97669	0	0	0	1	
98024	0	0	0	1	
110248	0	0	0	1	
128571	0	0	1	0	
185593	0	0	0	1	
^^^^^	^^^^^	^^^^^	^^^^^	^^^^^	
Total Freq	97	10	15	18	

# Questions?