

Arrests 2010 NTA analysis

```
##          used (Mb) gc trigger (Mb) max used (Mb)
## Ncells 497912 26.6   1079375 57.7   686460 36.7
## Vcells 928805  7.1    8388608 64.0   1877429 14.4
```

Preprocessing

Remove date and NTA variables, convert to factor location, month and KY_CD.

```
## 'data.frame':   419383 obs. of  15 variables:
## $ KY_CD       : Factor w/ 70 levels "101","102","103",...: 70 4 70 15 70 70 70 4 70 4 ...
## $ LAW_CAT_CD  : Factor w/ 5 levels "", "F", "I", "M",...: 1 2 4 2 4 2 4 2 4 2 ...
## $ AGE_GROUP   : Factor w/ 5 levels "<18","18-24",...: 3 2 3 1 4 4 3 2 2 3 ...
## $ PERP_SEX    : Factor w/ 2 levels "F", "M": 2 2 2 2 2 2 2 2 2 2 ...
## $ PERP_RACE   : Factor w/ 7 levels "AMERICAN INDIAN/ALASKAN NATIVE",...: 6 3 3 3 3 7 6 7 7 3 ...
## $ NTA2020     : Factor w/ 251 levels "BK0101","BK0102",...: 91 28 126 6 68 231 46 140 155 217 ...
## $ MONTH       : Factor w/ 12 levels "1","2","3","4",...: 1 11 3 12 12 12 11 11 10 9 ...
## $ GeoID       : Factor w/ 251 levels "BK0101","BK0102",...: 91 28 126 6 68 231 46 140 155 217 ...
## $ Pop1        : num  43885 76961 21140 24605 39214 ...
## $ Male.P      : num  44.4 44.7 49.3 48.2 46.8 48.9 45.1 48.8 49.5 47.2 ...
## $ MdAge       : num  46.1 33.2 39.1 34.8 29.3 35.3 34.1 34.1 34.7 37.8 ...
## $ Hsp1P       : num  17 12 8.2 17.8 69.1 30.6 20.1 52.2 28.2 18.6 ...
## $ WNHP        : num  68 9.2 65.1 47.8 1.5 25.3 8 10.9 47.2 6.4 ...
## $ BNHP        : num  7.5 74.3 4.5 20.7 27.5 35.3 66.1 32.2 4.6 48.3 ...
## $ ANHP        : num  5.3 1.9 19.8 10.1 0.8 5.2 3.2 2.2 16.4 17.1 ...
```

Check for NA

```
##      KY_CD LAW_CAT_CD AGE_GROUP PERP_SEX PERP_RACE NTA2020 MONTH
##      0         0         0         0         0         0         0
##      GeoID      Pop1      Male.P      MdAge      Hsp1P      WNHP      BNHP
##      0         0         2491      2489      2702      3111      3281
##      ANHP
##      4315
```

A possibility is to get rid of all NAs rows, the portion of deleted rows would be relatively small (of course we're introducing some bias here).

```
## [1] 0.9890935
```

Other possibilities would be to impute values for numerical variables (using median, mean or more sophisticated methods). For simplicity we just delete missing values rows.

Description

Ideally 2010 data are our training set and 2011 data are the test set. The goal of the analysis is to identify if some covariates are correlated with the arrests rate: more specifically if the response is well explained by some non spatial covariates alone, some spatial alone or interaction between the two.

A reasonable response variable would be the count of arrests divided by the local (space zone) population, also grouping by any other covariates value.

To get an idea of the dataset used on which models are tested a

```
## 'summarise()' has grouped output by 'KY_CD', 'LAW_CAT_CD', 'AGE_GROUP',  
## 'PERP_SEX', 'PERP_RACE', 'NTA2020', 'GeoID', 'Pop1', 'Male.P', 'MdAge',  
## 'Hsp1P', 'WNHP', 'BNHP'. You can override using the '.groups' argument.
```

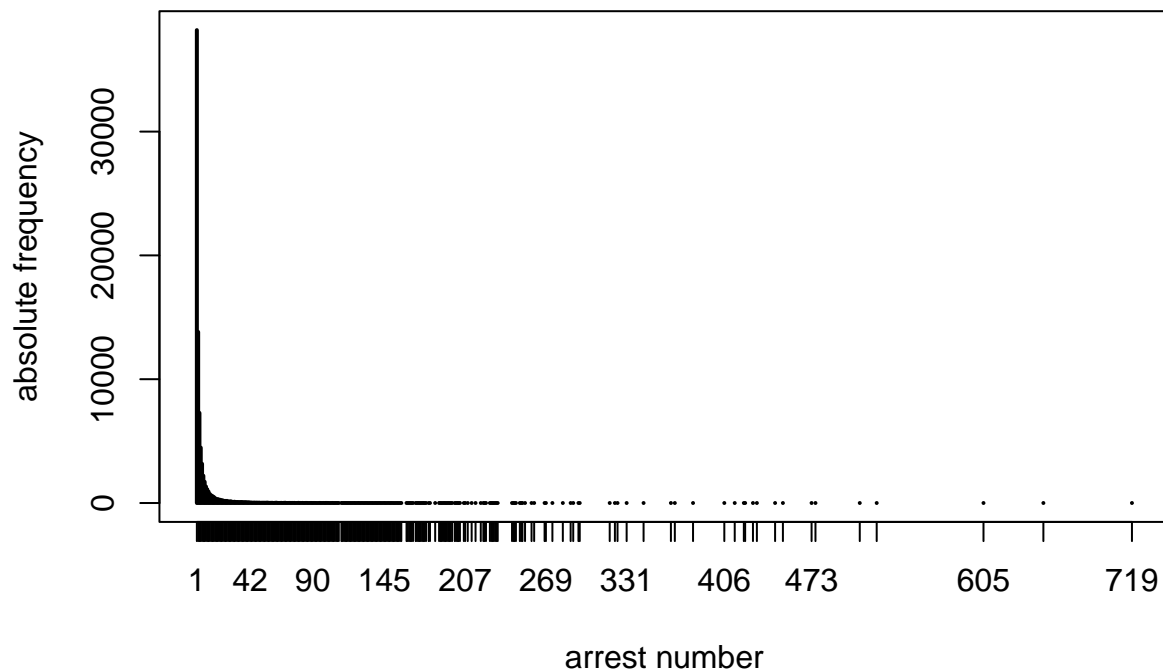
```
## [1] 81946      16
```

```
## [1] "KY_CD"      "LAW_CAT_CD" "AGE_GROUP"  "PERP_SEX"  "PERP_RACE"  
## [6] "NTA2020"    "GeoID"      "Pop1"      "Male.P"    "MdAge"  
## [11] "Hsp1P"     "WNHP"      "BNHP"      "ANHP"      "count"  
## [16] "y"
```

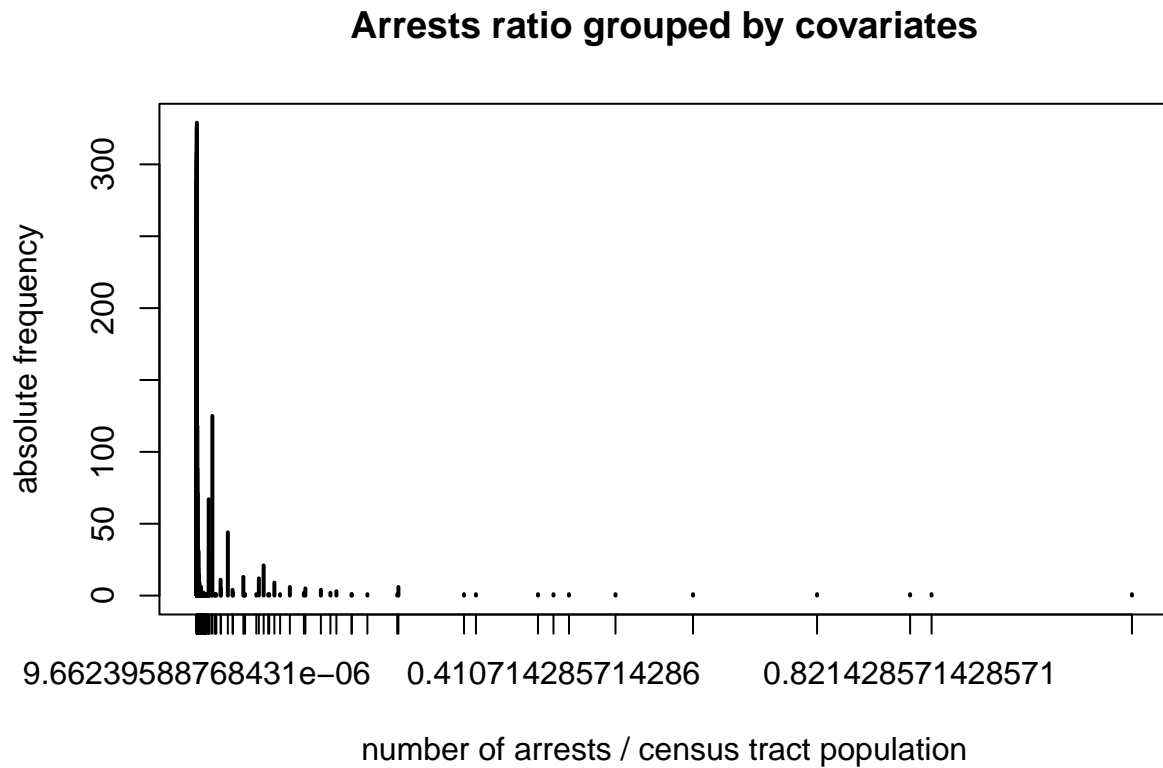
Still a huge number of observations compared to the number of variables, but what if we add interactions?

Let's look at the distribution of the counts

Arrests counts grouped by covariates



We can see an inflation of ones. The ratios present a similar table.



Let's count the hypothetical number of interaction terms if ones considers only interactions between spatial zones and selected arrests covariates along with the observations / number of parameter ratio (underestimate since there are other variables):

##	KY_CD	LAW_CAT_CD	AGE_GROUP	PERP_SEX	PERP_RACE	NTA2020	GeoID
##	70	5	5	2	7	209	209
##	Pop1	Male.P	MdAge	Hsp1P	WNHP	BNHP	ANHP
##	207	83	128	172	170	156	135
##	count	y					
##	248	5754					

Not including KY_CD:

```
## NTA2020
## 3971
```

```
## NTA2020
## 20.63611
```

Including KY_CD

```
## NTA2020
## 18601
```

```
## NTA2020
## 4.405462
```

We decide to not employ the MONTH time variable as a covariate but use it for a model selection method.

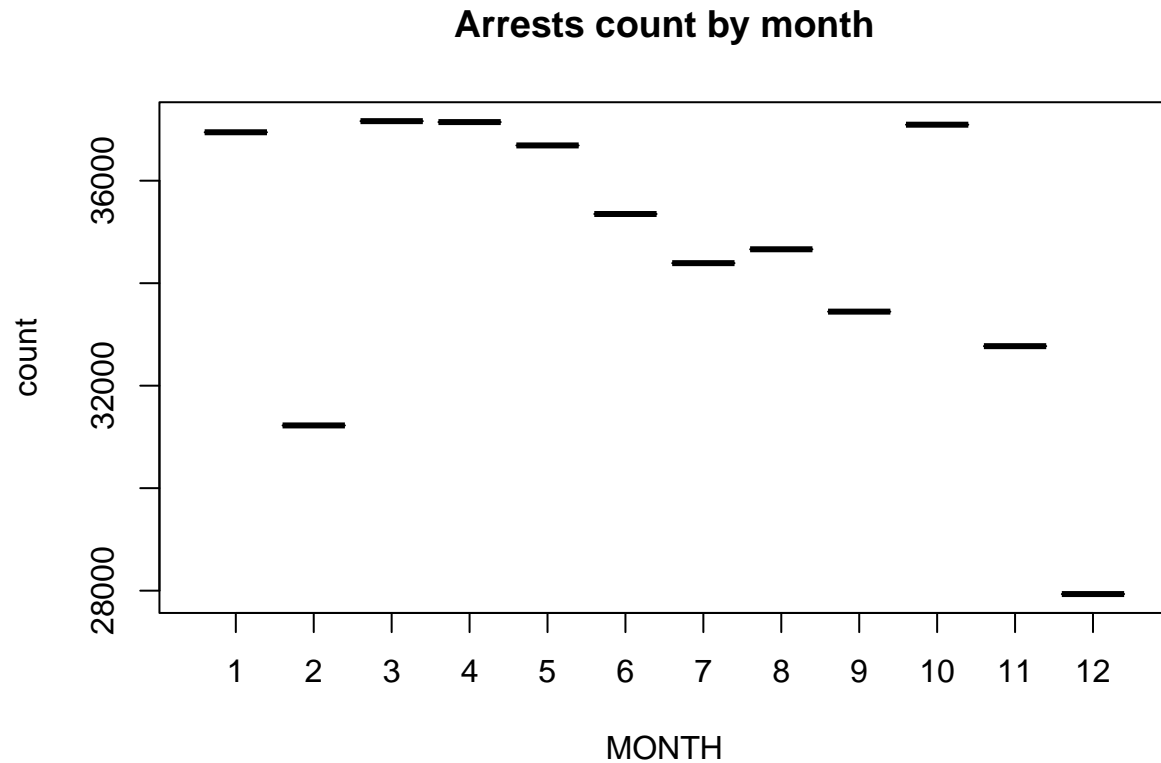
Variables description

Original dataset selected variables:

Census stratification variables:

Explorative analysis

Arrests count vs month



Arrests counts vs NTA

Arrest counts vs other covariates

Models

Model selection method

Given the previously described constraints, in order to be able to apply a cross validation (CV) selection method we choose to ignore the time (MONTH) factor using MONTH as index to create the CV folds as

described below. Choose k : the number of validation sets (example $k = 4$) each validation set is made by grouped observations of $12 / k$ (3) months and the months left are used to fit the model. To try to compensate and average for seasonal fluctuations the validation months are chosen as spaced as possible, for example, in the case $k = 4$ the first validation set is (january, may, september), the second set is (february, june, october), the third is (march, july, november) and the fourth is (april, august, december); in order to make each response comparable having used a different number of months a new response is defined as the arrests ratio divided by the number of months used in the grouping.

Define Month indexes

In order to simplify computations we remove the `KY_CD` variable (hoping `LAW_CAT_CD` will be sufficient to describe the crime type)

```
## 'summarise()' has grouped output by 'LAW_CAT_CD', 'AGE_GROUP', 'PERP_SEX',  
## 'PERP_RACE', 'NTA2020', 'GeoID', 'Pop1', 'Male.P', 'MdAge', 'Hsp1P', 'WNHP',  
## 'BNHP'. You can override using the '.groups' argument.
```

Error functions

Model matrices: omit `KY_CD` variables due to computational issues. Make a list of fit and validation sets:

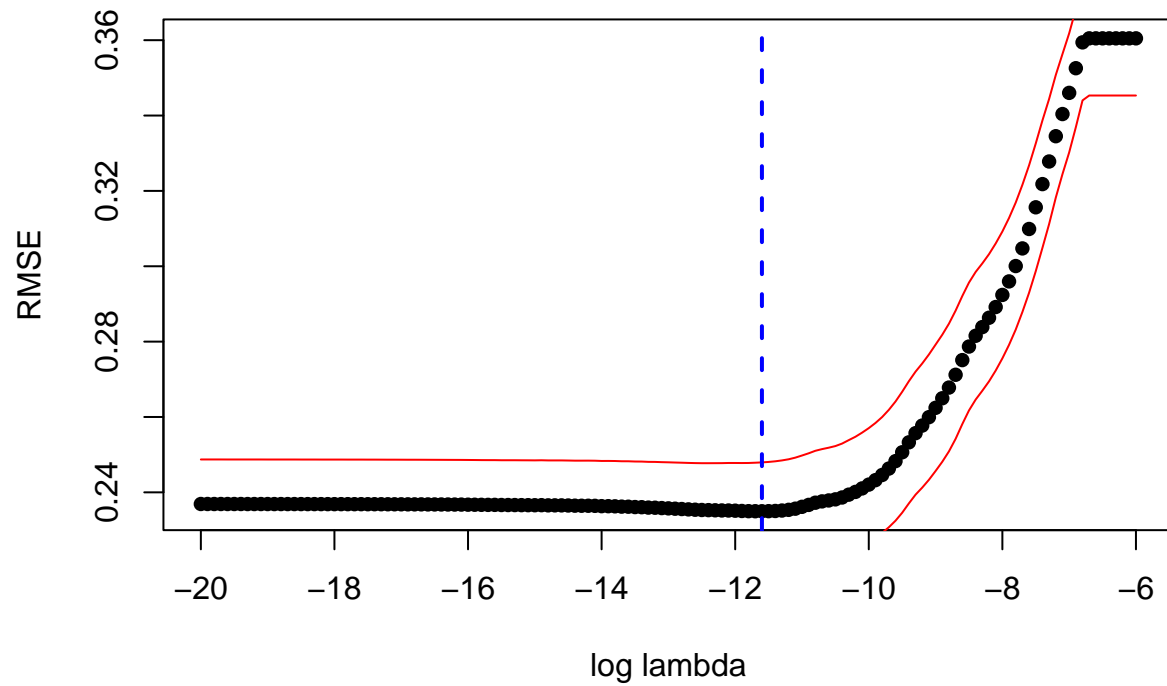
Note on quantitative covariates

The simplest assumption is to assume a linear (monotone) trend of the response as a function of quantitative covariates.

LASSO

```
## Loaded glmnet 4.1-8
```

LASSO CV error



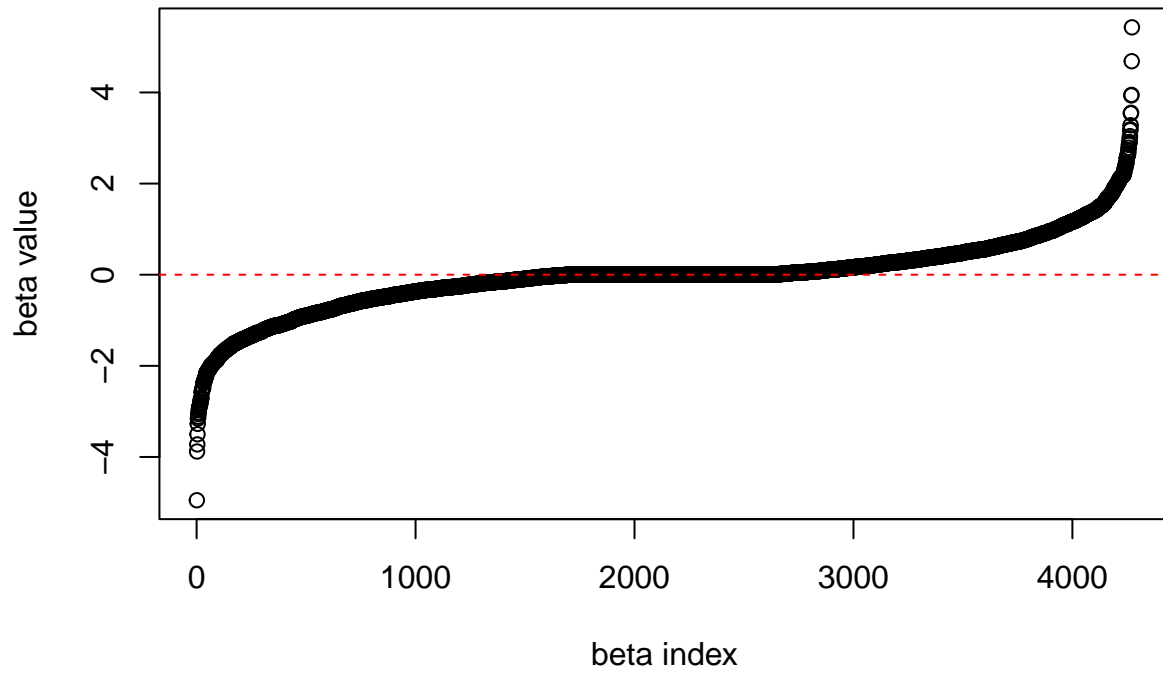
Bets λ is close to zero, so the best solution seems OLS classical solution.

Check beta: proportion of non zero beta among all betas

```
## [1] 0.803839
```

So the solution is not sparse even though many coefficients are close to zero.

Lasso lambda best coefficients



Elasticnet

Grouped LASSO

Scad MCP

Poisson LASSO

Poisson Elasticnet

Negative Binomial Lasso

Zero Inflated Lasso