

# Communities and crime

## Prediction of violent crime in the USA

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# Outline

1. The dataset
2. Preprocessing
3. Correlation analysis
4. Regression
5. Performance analysis
6. Conclusion

# The dataset

- ▶ Data sources:
  - ▶ Socio-economic data from the 1990 US Census
  - ▶ Law enforcement data from the 1990 US LEMAS survey
  - ▶ Crime data from the 1995 FBI UCR
- ▶ Creator: Michael Redmond, La Salle University, Philadelphia
- ▶ Date: 13th July, 2009

# The dataset

- ▶ Size: 1994 rows, 128 columns
- ▶ Example attributes: police officers per 100K population, median rent,...
- ▶ Goal: Prediction of violent crime in the USA

# The dataset

- ▶ As in most countries, violent crime is driven by socio-economic factors
- ▶ There seems to be a strong link between income inequality and crime
- ▶ Does our data confirm this?
- ▶ Which of these factors are of the highest importance?

# Preprocessing

- ▶ Before studying these correlations we must make sure our data is clean
- ▶ The values are already normalised, we must thus turn our attention to missing values

# Preprocessing

Column Name	Missing values	Column Name	Missing values
PolicReqPerOffic	1675(84%)	PolicAveOTWorked	1675(84%)
PolicPerPop	1675(84%)	RacialMatchCommPol	1675(84%)
PctPolicWhite	1675(84%)	PctPolicBlack	1675(84%)
PctPolicHisp	1675(84%)	PctPolicAsian	1675(84%)
PctPolicMinor	1675(84%)	OfficAssgnDrugUnits	1675(84%)
NumKindsDrugsSeiz	1675(84%)	LemasSwFTFieldPerPop	1675(84%)
LemasTotReqPerPop	1675(84%)	LemasSwFTFieldOps	1675(84%)
LemasSwFTPerPop	1675(84%)	PolicCars	1675(84%)
PolicOperBudg	1675(84%)	LemasPctPolicOnPatr	1675(84%)
LemasGangUnitDeploy	1675(84%)	LemasSwornFT	1675(84%)
PolicBudgPerPop	1675(84%)	LemasTotalReq	1675(84%)
OtherPerCap	1(0.05%)		

Table 1: Total number of rows: 1994

# Preprocessing

Listwise deletion:

- ▶ = Method for handling missing data
- ▶ Delete columns or rows that have any missing data at all
- ▶ Very simple method to deal with missing data
- ▶ Loss of information, and thus loss in the quality of the prediction
- ▶ Good method so long as we retain sufficient power after deletion



# Preprocessing

## Imputation:

- ▶ = Method for handling missing data
- ▶ Replace missing values with substituted data
- ▶ Ex: Median, Average,...
- ▶ Less loss of information
- ▶ May introduce bias in the correlation
- ▶ Leads to lower standard errors, which may lead to Type 1 errors

# Preprocessing

Why can we use listwise deletion on the columns with 84% of missing data?

- ▶ Most of the entries are missing, thus we don't lose too much data
- ▶ We have very little data left to base our imputation on, which would make it a bad choice

# Preprocessing

How do we handle the one missing entry in the OtherPerCap column?

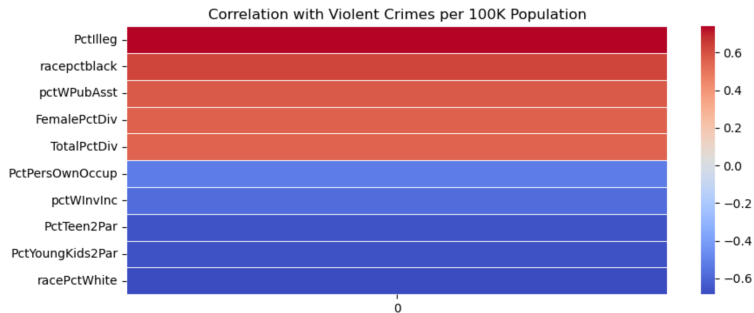
- ▶ Delete the column, but we would lose 1994 entries
- ▶ Use imputation, which should work well in this case
- ▶ Delete the row, and lose one out of 1994 rows = minimal loss of information

We deleted the row containing the missing value to keep our code as simple as we can

# Correlation analysis

- ▶ Before applying a regression algorithm, it would be interesting to check which predictors are significant
- ▶ Thus we plot a graph with the correlation between the predictors and violent crime
- ▶ We exclude all predictors with a correlation that lies close to 0

# Correlation analysis



# Correlation analysis

INSERT CLOSER ANALYSIS OF SOME OF PREDICTORS WITH  
BEST CORRELATION (OR INVERSE CORRELATION)

# Regression

- ▶ Given that our response variable is continuous, we have to perform regression to predict it
- ▶ Idea: Use random forest regression

# Regression

What is random forest regression?

- ▶ Based on ensemble learning
  - ▶ = method where multiple ML algorithms are combined
- ▶ Utilises subsets of the data to create multiple trees (= bagging)
- ▶ The obtained results are averaged to create the final result



# Regression

What are the advantages of random forest regression?

- ▶ Performs well with little to no hyperparameter tuning
- ▶ Rarely overfits
- ▶ Low sensitivity to noise
- ▶ Good at noticing general patterns in the data

# Regression

What are the disadvantages of random forest regression?

- ▶ Bad at extrapolation
- ▶ Makes predictions only in the range of data contained in the training set

# Regression

Why can we use random forest regression?

- ▶ Our data seems to be diverse enough to cover a realistic range of crime rates
- ▶ It seems unlikely that we might have to predict a crime rate that is much higher than in our training set
- ▶ We have quite a few predictors left, even after cleaning, thus overfitting could be an issue

# Sources

- ▶ [https://en.wikipedia.org/wiki/Listwise\\_deletion](https://en.wikipedia.org/wiki/Listwise_deletion)
- ▶ [https://en.wikipedia.org/wiki/Imputation\\_\(statistics\)](https://en.wikipedia.org/wiki/Imputation_(statistics))
- ▶ <https://www.theanalysisfactor.com/mean-imputation/>
- ▶ <https://www.theanalysisfactor.com/when-listwise-deletion-works/>
- ▶ <https://cnvrg.io/random-forest-regression/>
- ▶ [https://minds.wisconsin.edu/bitstream/handle/1793/77496/Violent%](https://minds.wisconsin.edu/bitstream/handle/1793/77496/Violent%20Crime%20in%20the%20United%20States.pdf)