# Final Project

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# Predicting Violent Crime Rates

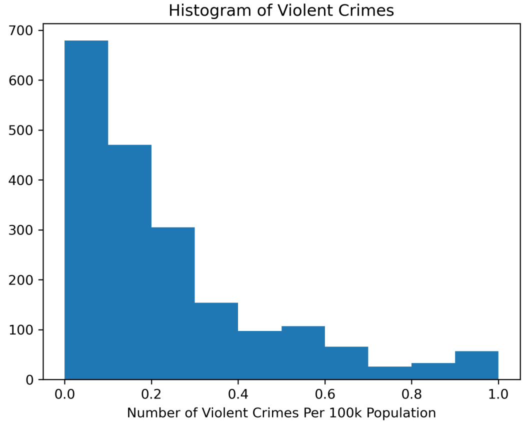
# Dataset

- Data hosted on the University of California Irvine machine learning repository (Redmond 2009)
- Combines data from three datasets, the 1990 Census, 1995 FBI Uniform Crime Report (UCR), and the 1990 US Law Enforcement Management and Administrative Statistics Survey (LEMAS)
- Contain information about socio-economic indicators (e.g., median family income) and crime/law enforcement (e.g., per capita number of police officers)
- 1994 observations and 122 predictive features.

# Problem Statement

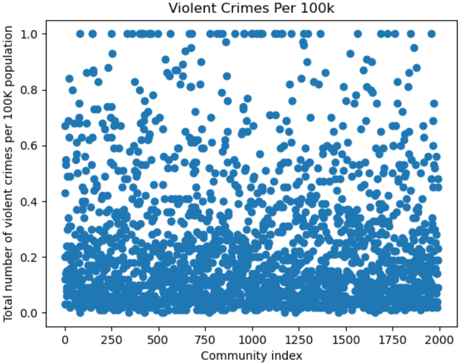
- In this project, we want to predict violent crime rates from a variety of features using the “Communities and Crime” dataset
- Main challenges are processing the dataset, choosing predictors, and models

# Target



Histogram of Violent Crimes
700
600
500
400
300
200
100
0
0.0
0.2
0.4
0.6
0.8
1.0
Number of Violent Crimes Per 100k Population

# Target



Violent Crimes Per 100k
Total number of violent crimes per 100K population
1.0
0.8
0.6
0.4
0.2
0.0
0
250
500
750
1000
1250
1500
1750
2000
Community index

# Plan

- Choose a method for dealing with missing data
- Filter features to choose the most relevant
- Pick the best model
  - Compare MLP with classical machine learning methods

# Contribution

- This data set does not have any published papers relevant to it (Redmond 2009)
  - So any analysis with this particular data set is new
- There is a large literature on the use of machine learning in so-called "predictive policing" (Hardyns and Rummens 2018)
- Many predictive policing systems use a single method ML method, like gradient boosting
- We have tried many different methods and compared them

# Missing Data

- Data are “missing not at random” (Rubin 1976)
- Impute data using *MICE* algorithm (Van Buuren 2018)
  - Implemented as part of `MultipeImputer`
- Check analysis as part of robustness check

# Preprocessing

- Filter features based on correlation, drop variables with correlation greater than a cutoff value
- Algorithm for removing highly correlated features is taken from (Kuhn, Johnson, and others 2013, 26:47)

1. Calculate correlation matrix (`.corr()`)
2. Find two predictors with largest absolute pairwise correlation (A and B)
3. Find average correlation for all features with A and all features with B
4. If A greater than B, remove A. Else, B
5. Repeat until no correlations above threshold

# Solver

- Rather than stochastic gradient descent, use `L-BFGS` solver (limited memory Broyden–Fletcher–Goldfarb–Shanno) (Aggarwal and others 2018, 148)
- Approximates Newton method:

$$\mathbf{W}(t+1) = \mathbf{W}(t) - \mathbf{H}^{-1}\nabla F(t)$$

- Replace $\mathbf{H}^{-1}$ with an approximation $\mathbf{G}(t)$

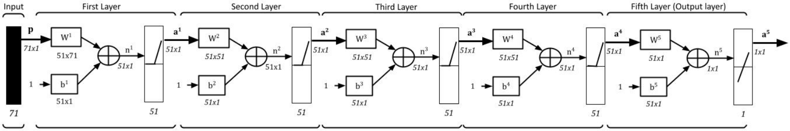
$$\mathbf{W}(t+1) = \mathbf{W}(t) - \alpha(t)\mathbf{G}(t)\nabla F(t)$$

# Hyperparameter Tuning

- For every model type, there are many parameters to choose
  - For MLP, can choose number of hidden layers, activation function, learning rate, etc.
- We use 5-fold cross validation to choose hyperparameters for each model type
- Implemented with `GridSearchCV`, scored by `neg_mean_squared_error`

# Results

# Model Architecture




71-51-51-51-51-1

Figure 1: Chosen MLP

# Results

Table 1: Model Performance for Non-Imputed Data

| Model Type | Best 5-Fold MSE | Test MSE |
|---|---:|---:|
| SVR | 0.0186 | 0.0203 |
| DTR | 0.0356 | 0.0453 |
| RFR | 0.0181 | 0.0187 |
| MLP | 0.0180 | 0.0130 |

Table 2: Model Performance for Imputed Data

| Model Type | Best 5-Fold MSE | Test MSE |
|---|---:|---:|
| SVR | 0.0185 | 0.0199 |
| DTR | 0.0352 | 0.0389 |
| RFR | 0.0178 | 0.0187 |
| MLP | 0.0181 | 0.0167 |

# Predicted Values

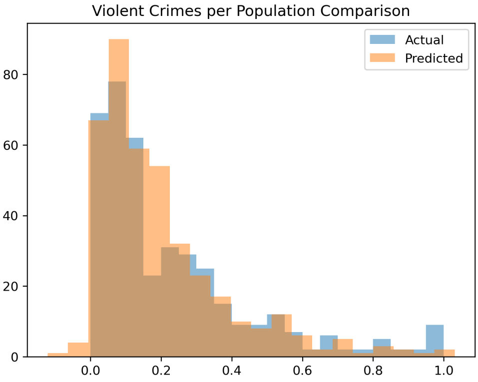
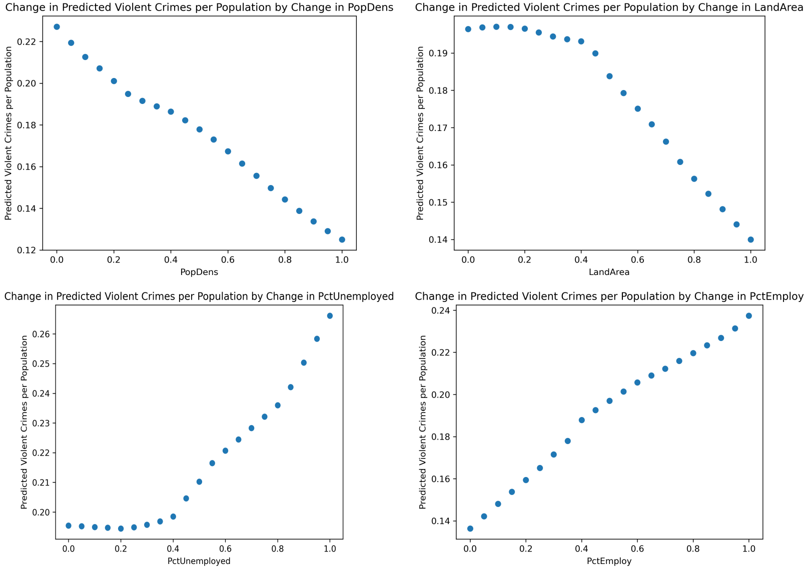



Figure 2: Violent Crime Per Population Comparison (Test Data)

# Predicted Crime Rate Changes



# Further Work

- Better data imputation algorithm
  - `IterativeImputer` has multiple estimations methods or `KNNImputer`
- More up to date data
  - Potentially incorporate time series data
- More comprehensive hyperparameter grid to search

# References I

Aggarwal, Charu C, and others. 2018. "Neural Networks and Deep Learning." *Springer* 10. Springer: 978–3.

Hardyns, Wim, and Anneleen Rummens. 2018. "Predictive Policing as a New Tool for Law Enforcement? Recent Developments and Challenges." *European Journal on Criminal Policy and Research* 24 (3). Springer: 201–18.

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Redmond, Michael. 2009. "Communities and Crime." https://archive.ics.uci.edu/ml/datasets/Communities+and+Crime.

Rubin, Donald B. 1976. "Inference and Missing Data." *Biometrika* 63 (3). Oxford University Press: 581–92.

Van Buuren, Stef. 2018. *Flexible Imputation of Missing Data*. CRC press.