Crime Category Prediction of Cities Using an Ensemble of Various Classifiers

January 10, 2018

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Motivation

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4. Evaluate the results
   - Accuracy, Precision, Recall, F-Measure

Dataset

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> Union of three subsets containing real crime data

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- **crime category** (added by us)

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  - The prediction of crime activity within the clusters was performed by an artificial neural network

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  - Reduce the dimensionality of the feature space

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- Each cluster will be assigned a label (e.g. "High", "Medium", "Low",... crime rate)

Assignment of Class Labels

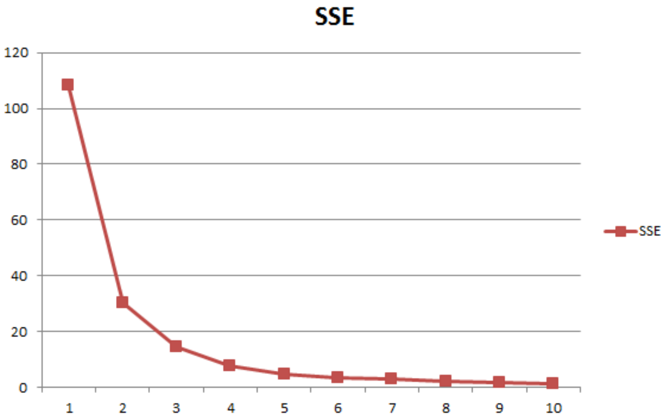

Figure: Sum of the squared errors for different choices of k

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  - High: $(56\%; 100\%]$

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- The percentage boundaries are extracted from the clusters
  - Low: $[0\%; 22\%]$
  - Medium: $(22\%; 56\%]$
  - High: $(56\%; 100\%]$
- Depending on the group it falls into, each instance (city) can now be assigned a label

Feature Selection

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- Add some features with high correlation and remove some with low correlation

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> Compare the judgement ranking with the correlation ranking

> Add some features with high correlation and remove some with low correlation
   > E.g. the attribute "population" was removed because of a correlation near zero

Experimental Results

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Approaches and Settings

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> k-Nearest Neighbors

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k-Nearest Neighbors

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k-Nearest Neighbors

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- parameter search on a leave-one-out cross validation
- k=30 best (accuracy)

k-Nearest Neighbors

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k-Nearest Neighbors

> parameter search on a leave-one-out cross validation
> k=30 best (accuracy)
> distance measure = euclidean distance
> no distance weighting => better results

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Naïve Bayes

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> Useful in may areas (text classification, medical diagnosis, ...)
> Still employed although the features are obviously not independent
    > For example "median income" is clearly related to "number of people below the poverty level"

Decision Tree

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> pruned J48-decision tree

Decision Tree

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Decision Tree

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- found by utilizing WEKAs capabilities of linear parameter search

Neural Network

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> multilayer perceptron

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- 13 input neurons (features)

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- multilayer perceptron
- 13 input neurons (features)
- hidden layer of 17 neurons
- output layer with three neurons (classes)
- learning rate: $\alpha = 0.1$
- momentum: $m = 0.1$ (backpropagation algorithm)
- linear search for parameters: hidden neurons, learning rate and momentum

Ensemble

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> Merge all models into an ensemble
> Goal: Combine the strengths of the different classifiers
> Choice of ensemble was found by conducting a majority voting

Results

> The results of each classifier were evaluated using 10-fold cross validation

Results

- The results of each classifier were evaluated using 10-fold cross validation
- Common evaluation metrics allow for comparison
  - Accuracy, Precision, Recall, F-Measure

Results

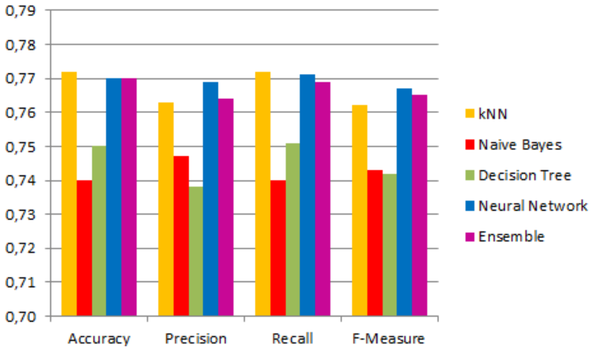

Figure: Evaluation metrics of the different classifiers

Results

Table: Confusion matrix of the ensemble

classified →	**Low**	**Medium**	**High**	Total
Low	1125	126	8	1259
Medium	160	305	57	522
High	15	95	103	213
Total	1300	526	168	1994

Recall

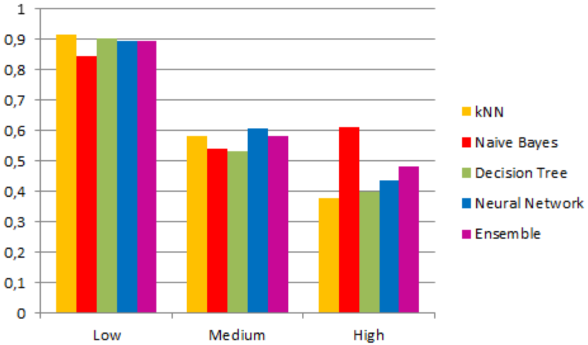

Figure: Recall of the different classifiers

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  > Never reached top spot in any category

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  - Emphasize strengths of one classifier (e.g. high recall of Naïve Bayes), mitigate weaknesses of another

Discussion and Outlook

Thank you very much for listening!
Any questions left?

J. Andrew Ware Jonathan J. Corcoran Ian D. Wilson. "Predicting the geo-temporal variations of crime and disorder". English. In: *International Journal of Forecasting* 19(4) (Oct. 2003), pp. 623–634. URL: http://www.sciencedirect.com/science/article/pii/S0169207003000955.

Nasim Khanahmadliravi. "An Experimental Study of Classification Algorithms for Crime Prediction". English. In: *Indian Journal of Science and Technology* 6(3) (Mar. 2013), pp. 4219–4225. ISSN: 0974-6846. URL: http://52.172.159.94/index.php/indjst/article/download/31230/27028.