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Crime Category Prediction of Cities Using an Ensemble of Various Classifiers

January 10, 2018

Hardy Hambsch Marius Nolden Jessica Ahring Christian Peters

Motivation

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   - Accuracy, Precision, Recall, F-Measure

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

Assignment of Class Labels

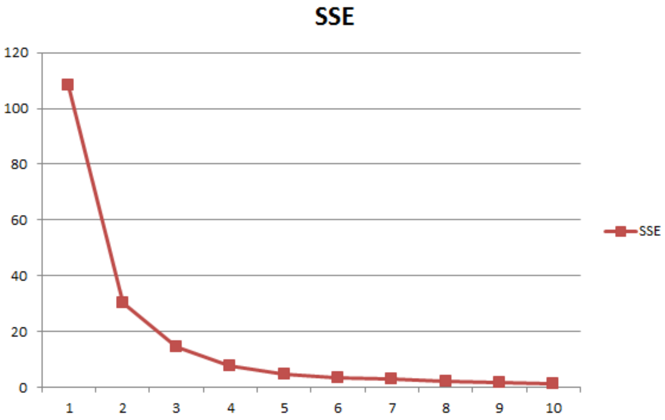

Figure: Sum of the squared errors for different choices of k

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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

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1. Create a ranking by judgement of significance

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> 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

Approaches and Settings

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- Ensemble

k-Nearest Neighbors

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> parameter search on a leave-one-out cross validation

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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

Naïve Bayes

Another approach is the Naïve Bayes classifier. Despite some attributes obviously not being independent, it was still employed because it proved to be useful in other areas as well.

Decision Tree

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- found by utilizing WEKAs capabilities of linear parameter search

Neural Network

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- multilayer perceptron
- 13 input neurons (features)
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- 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

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- ensemble was found by conducting a majority voting

Results

> 10-fold cross validation

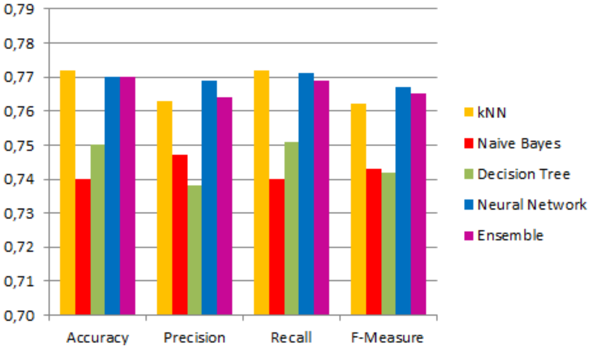

Figure: Evaluation metrics of the different classifiers

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

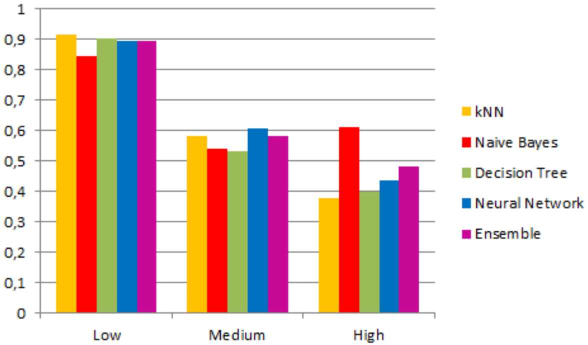

Figure: Recall of the different classifiers

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  - Always among the best
  - Never reached top spot in any category

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  - Improve the results by changing the weights

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- Can this be improved?
  - In our case, each base learner had an equal weight
  - Improve the results by changing the weights
  - 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?

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