CITS3401 Data Exploration and Mining
Project 2

Wine Classification

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Introduction

The project specified that we are to develop several classifiers for wines using different classification methods to compare how machine learning performs compared to experts when rating different wines. The initial data is split into two groups, red wine and white wine, available from the UCI Machine Learning Repository[1]. Data analysis was done using Weka[2], data mining software created by Machine Learning Group at the University of Waikato, New Zealand. Specifically, we are using the classification and clustering tools in Weka Explorer for analysis.

Data Preprocessing

The initial data provided was in two files, `winequality-red.csv` and `winequality-white.csv`, that where converted to Weka's ARFF file format using an online conversion tool[3]. This tool was used to output two datasets, dataset 1 (`ds1-red.arff` and `ds1-white.arff`) and dataset 2 (`ds2-red.arff` and `ds2-white.arff`). Dataset 1 contains all the information that was in the original data, and is used to create the classifier. The fields in this dataset are numeric, apart from the quality which is nominal, making it is possible to group wines that receive the same rankings in Weka. Dataset 2 is contains all the numerical information from the original data and does not contain any information about the rankings from the wine tasters. The aim is to cluster these so that the wines fall into groups similar to the quality attribute of dataset 1.

Clustering

Dataset 2 requires clustering before it can be classified as the quality attribute of each data point has been removed. Simple K means clustering was used and after experimenting, fixed acidity, volatile acidity, citric acid, and density were ignored for the red wine data. This gave a roughly similar distrubution to the qualities found in the red wine dataset. In the white wine dataset, ignoring the different attributes has very little effect on the clustering. After ignoring different combinations of attributes, it does not seem possible to cluster the data points into a similar distrubution to the initial data. Comparing the clustering with the red wines quality information shows a 35% accuracy in the groupings, while for the clustered white wines there is only 25% accuracy.

`Red Wine`

```
Scheme:weka.clusterers.SimpleKMeans -N 6 -A
"weka.core.EuclideanDistance -R first-last" -I 500 -S 10

Clustered Instances

0       632 ( 40%)
1       128 (  8%)
2       196 ( 12%)
3        32 (  2%)
4       339 ( 21%)
5       272 ( 17%)
```

White Wine

```
Scheme:weka.clusterers.SimpleKMeans -N 7 -A
"weka.core.EuclideanDistance -R first-last" -I 500 -S 10
Clustered Instances

0      1093 ( 22%)
1       536 ( 11%)
2       832 ( 17%)
3       569 ( 12%)
4       885 ( 18%)
5       658 ( 13%)
6       325 (  7%)
```

Classification

Naive Bayesian

Naive Bayes classifiers are simple to implement, fast, and are used in real world situations such as spam filters. They work by looking at the traits of an object, and using each individual trait to determine how likely it is that the object falls into a specific classification. Their downside is that they assume the presence or absence of particular traits has no affect on the classification. We used cross-validation for Naive Bayes with 10 folds in Weka to calculate classfify all the wines, and compared the classifications with the quality fields. Experimentation showed that increasing the number of folds for the red wine only had minimal effect on the accuracy of the classification.

Dataset 1

Red Wine

```
Scheme:weka.classifiers.bayes.NaiveBayes
Relation:     ds1red
Instances:    1599
Attributes:   12
Test mode:10-fold cross-validation

Correctly Classified Instances         880               55.0344 %
Incorrectly Classified Instances       719               44.9656 %
Kappa statistic                          0.311
Mean absolute error                      0.1763
Root mean squared error                  0.3198
Relative absolute error                 82.1845 %
Root relative squared error             97.7154 %
Total Number of Instances             1599
```

White Wine

```
Scheme:weka.classifiers.bayes.NaiveBayes
Relation:     ds1white
Instances:    4898
Attributes:   12
Test mode:10-fold cross-validation

orrectly Classified Instances        2168               44.263  %
Incorrectly Classified Instances      2730                55.737  %
Kappa statistic                          0.2169
Mean absolute error                      0.1721
Root mean squared error                  0.3221
Relative absolute error                 89.1485 %
Root relative squared error            103.6855 %
Total Number of Instances             4898
```

Dataset 2

Red Wine

```
Scheme:weka.classifiers.bayes.NaiveBayes
Relation:     ds2red_clustered-weka.filters.unsupervised.attribute.Remove-R1
Instances:    1599
Attributes:   12
Test mode:10-fold cross-validation

Correctly Classified Instances        1424               89.0557 %
Incorrectly Classified Instances       175                10.9443 %
Kappa statistic                          0.8548
Mean absolute error                      0.0534
Root mean squared error                  0.1698
Relative absolute error                 21.401  %
Root relative squared error             48.0797 %
Total Number of Instances             1599
```

White Wine

```
Scheme:weka.classifiers.bayes.NaiveBayes
Relation:   ds2white_clustered-weka.filters.unsupervised.attribute.Remove-R1
Instances:  4898
Attributes: 12
Test mode:10-fold cross-validation

Correctly Classified Instances        4267               87.1172 %
Incorrectly Classified Instances       631                12.8828 %
Kappa statistic                          0.8467
Mean absolute error                      0.0594
Root mean squared error                  0.1667
Relative absolute error                 24.7449 %
Root relative squared error             48.0952 %
Total Number of Instances             4898
```

Support Vector Machine

Support Vector Machine's are learning models and algorithms that analyze data and find patterns, then use the patterns for classification of data. Unlike the Naive Bayesian classifier, the support vector machine is a non-probabilistic classifier, meaning that it will not provide uncertainty for the results. This means that each different category is separated by as large a gap as possible.

Dataset 1

Dataset 2

Neural Network

Neural Networks are based off of animal's central nervous systems, by using several input sensors that transform the data before handing it on to another neuron. The neurons are connected together in a network and work simultaneously , rather then sequentially, to process the data. Real world applications for neural networks include speech and handwriting recognition.

Dataset 1

Dataset 2

Results

The project stated it wanted dataset 1, the unmodified dataset, and dataset 2, the clustered dataset, compared through the use of classifiers.

- Red wine dataset is not very spread out
- White wine distribution was. Looks like a bell curve
- only physiochemical inputs, no price, brand, grape type included. Psycology thingiemabobs.

Bibliography

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[6] Non-Probabilistic Classication Methods. 2014. Non-Probabilistic Classication Methods. [ONLINE] Available at: `http://www.dcs.gla.ac.uk/~girolami/Machine_Learning_Module_2006/week_5/Lectures/wk_5.pdf`. [Accessed 01 June 2014].