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# Appendices

The appendices in this section provide definitions of the symbols used, general definitions of statistical measures and descriptive statistics for the datasets used in the experiments. Details of correlation measurements, details for the 5NN aggregation algorithm, and OVA and pVn model performance are provided. Information is also provided on suggestions on how to use commonly available statistical and database software to implement some of the steps for the proposed feature and training dataset selection methods. Finally, a list of publications and conference presentations arising from the research is given. The table below summarises the appendix contents.

*Table of appendices*

| Appendix | Title | Description |
|---|---|---|
| A | Definition of symbols | Definition of symbols used in the thesis |
| B | Definitions of statistical measures | Definitions of statistical measures used in the thesis |
| C | Descriptive statistics for datasets | Descriptive statistics for forest cover type, KDD Cup 1999, Abalaone3C and mushroom |
| D | Correlation measurements | Details of correlation measurements and feature selection of chapter 4 |
| E | Algorithm for 5NN aggregation | Details of algorithm for the combination of 5NN base model predictions |
| F | Predictive performance of OVA and pVn models | Detailed results for accuracy for single and aggregate models for chapters 7 and 8. |
| G | ROC analysis details | Computation of the AUC for one-versus-rest ROC analysis. Details of AUC computation results. |
| H | Using statistical and database software to implement dataset selection methods | Suggestions for using commonly available statistical and database software to implement dataset selection |
| I | Publications and Conference Presentations | Publications and conference presentations arising out of the work reported in this thesis |

# Appendix A

# Definition of symbols

*Table A.1: Symbols used in the thesis*

| Symbol | Meaning |
|---|---|
| $accuracy$ | The predictive accuracy of a model |
| $B_i,..,B_v$ | Binary features created through the process of binarisation of a qualitative feature with *v* levels |
| $corr(X,Y)$ | The sample correlation coefficient between two random variables *X* and *Y* |
| $corr_{cf}(f)$ | The sample correlation coefficient between a feature *f* and a class variable *C* |
| $corr_{ff}(f)$ | The mean correlation between feature *f* and all other currently selected features |
| $c_1,\ldots,c_k$ | The *k* levels of a class variable (number of classes for a prediction task) |
| $C$ | A class variable for classification |
| $conf$ | Probabilistic score assigned by a model to a class prediction as the level of confidence in the prediction |
| $d$ | The number of predictive features (variables) that define the *d*-dimensional instance space for classification modeling |
| $1-\delta$ | The probability of a learner being able to induce a hypothesis from data as in PAC |
| $error$ | The prediction error of a model |
| $error_D, error_R$ | Error difference and error ratio for measuring performance gains |
| $error_S, error_A$ | Prediction errors of a single model and aggregate model respectively |
| $\varepsilon$ | Prediction error as in PAC |
| $E$ | Entropy function |
| $f$ | A feature (predictor) used in predictive modeling |
| $\phi$ | The phi coefficient for measuring the level of association between two qualitative variables |
| $g_i$ | A region of the instance space |
| $G$ | The Gini concentration coefficient |
| $h$ | A hypothesis as defined in machine learning |
| $H$ | A set of hypotheses as defined in machine learning |
| $H_0$ and $H_a$ | The null hypothesis and alternative hypotheses for statistical hypothesis testing |
| $k$ | Number of classes for a classification problem |
| $K$ | Number of folds for cross validation |
| $L_1,..,L_V$ | Levels of a qualitative (nominal or ordinal) variable |
| $\lambda$ | Cut-off score value for ROC analysis |

| Table A.1 continued | |
|---|---|
| Symbol | Meaning |
| $m$ | A mapping or a function |
| $M_A$ | General reference to a predictive model |
| $\mu_A$ | The population mean value of predictive accuracy of a model A |
| $n$ | The size of a sample taken from a parent dataset |
| $n_t$ | For sequential random sampling, $n_t$ is the number of records already selected |
| $N$ | The size of the parent dataset / database from which samples are taken |
| $ova_i$ | The i$^{th}$ sub-problem for the prediction of class $c_i$ in OVA classification |
| $p$ | Probability of obtaining an experimental result given that the null hypothesis is true (p value) |
| $P$ | Percentage value for a confidence interval (*P%* confidence interval) |
| $P_r$ | Probability |
| *PT* | The number of partitions of a parent dataset |
| *pred* | Output of a predictive model |
| $\pi_c$ and $\pi_d$ | The probabilities of concordance and discordance used in the computation of Kendall's tau |
| $r_{XY}$ , $r$ | Pearson's sample correlation coefficient for two random variables *X* and *Y* |
| $\tau_{XY}$ | Kendall's sample correlation coefficient for two random variables X and Y |
| $R^d$ | Super domain of real values for the random variables $X_1,..X_d$ |
| *RMsize, RQsize* | For sequential random sampling, RMsize is the number of records still to be processed; RQsize is the number of records required for the sample |
| $S_X$ | The sample standard deviation for random variable X |
| *SU* | Symmetrical uncertainty coefficient |
| $\sigma_X$ | The population standard deviation for random variable X |
| *si and spi* | Situations for feature subset search |
| $t$ | For sequential random sampling, t is the number of records processed so far |
| $T$ | The *T* statistic for statistical hypothesis testing |
| $u$ | Number of unselected features for heuristic feature subset search |
| $v$ | Number of levels for a qualitative variable |
| $V$ | Cramer's V statistic for measuring the level of association between two qualitative variables |
| *VC(H)* | The Vapnik-Chervonenkis dimension of a set of hypotheses *H* for a learning task |
| $w$ | Number of features currently selected/processed by a feature selection method/algorithm |
| $W$ | Number of candidate features for heuristic feature subset search |

| Table A1 continued | |
|---|---|
| Symbol | Meaning |
| ***x*** *and* $x_1,..x_d$ | A vector of predictive features (predictor variable ) values ( an instance) |
| $x_q$ | A query (or test) instance to be classified / assigned a predicted value |
| $X, Y$ | Random variables |
| $Z$ | The Z statistic for statistical hypothesis testing |
| $Z_P$ | Constant for the calculation of the *P%* confidence interval of the mean |
| $z\%$ | Percentage of values to remove from each tail when winsorising variable values |
| **Confusion matrix and ROC analysis symbols:** | |
| $Pos$ | Total number of positive instances |
| $Neg$ | Total number of negative instances |
| $TP$ | Number of positive instances predicted as positive |
| $FN$ | Number of positive instances predicted as negative |
| $TN$ | Number of negative instances predicted as negative |
| $FP$ | Number of negative instances predicted as positive |
| $TPRATE$ | Fraction of the positive instances predicted as positive |
| $FNRATE$ | Fraction of the positive instances predicted as negative |
| $TNRATE$ | Fraction of the negative instances predicted as negative |
| $FPRATE$ | Fraction of the negative instances predicted as positive |
| $YRATE$ | Fraction of test instances predicted as positive (used for lift analysis) |

# Appendix B

# Definitions of statistical measures

A detailed discussion of the statistical measures used in this thesis is provided in this appendix. The entropy measure, Gini index of concentration, and measures of association (correlation) were used in the discussions of chapters 3, 4, 5 and 7.

## B.1 Entropy definitions

The entropy function *E(X)* (Giudici, 2003; Shanon & Weaver, 1962) measures the amount of uncertainty, heterogeneity, information or randomness in the values of the qualitative or quantitative discrete random variable *X* and is defined as

$$E(X) = -\sum_i P_r(x_i)\log_2 P_r(x_i) \tag{B.1}$$

where $P_r(x_i)$ which is used as a shorthand notation for $P_r(X = L_i)$ is the probability that variable *X* has the value (level) $L_i$. The entropy of the random variable *X*, conditioned on the values of a second random variable *Y* is denoted as *E(X|Y)* and is defined as

$$E(X \mid Y) = -\sum_j P_r(y_j)\sum_i P_r(x_i \mid y_j)\log_2 P_r(x_i \mid y_j) \tag{B.2}$$

where $P_r(x_i \mid y_i)$ which is used as a shorthand for $P_r\big((X = L_i) \mid (Y = L_j)\big)$ is the conditional probability that random variable *X* has the value (level) $L_i$ given that random variable *Y* has the value (level) $L_j$ and is defined as

$$P_r(x_i \mid y_j) = \frac{P_r(x_i, y_j)}{P_r(y_j)} \tag{B.3}$$

where $P_r(x_i, y_j)$ is the probability of values $x_i$ and $y_j$ appearing together. The joint entropy of two random variables *X* and *Y* denoted as *E(X,Y)* is defined as

$$E(X,Y) = -\sum_{i} P_r(x_i, y_j)\log_2 P_r(x_i, y_j) \quad \text{(B.4)}$$

The difference between the entropy of *X, E(X)* and the entropy of *X* conditioned on *Y*, *E(X|Y)* is called the information gain *IG(X,Y)* and is defined as

$$IG(X,Y) = E(X) - E(X \mid Y) \quad \text{(B.5)}$$

$$IG(X,Y) = E(Y) - E(Y \mid X) \quad \text{(B.6)}$$

$$IG(X,Y) = E(X) + E(Y) - E(X,Y) \quad \text{(B.7)}$$

The information gain measures the amount of reduction in the entropy of *X* when the values of *X* are grouped based on the values of *Y*. As indicated by the equations (B.5) and (B.6), information gain *IG(X,Y)* is a symmetric measure from which the symmetrical uncertainty coefficient *SU* is derived. The *SU* coefficient is defined as

$$SU = 2.0x\left[\frac{IG(X,Y)}{E(X) + E(Y)}\right] \quad \text{(B.8)}$$

The SU coefficient was used for the experiments of chapters 5 and 7 as a measure of correlation (association) for qualitative features.

## B.2 Measures of association

### B.2.1 Pearson's correlation coefficient

Pearson's sample correlation coefficient, *r* (Wilcox, 2001), between two random variables *X* and *Y* is defined as

$$r_{XY} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{(n-1)S_X S_Y} \quad \text{(B.9)}$$

where $S_X$ and $S_Y$ are the standard deviations of *X* and *Y* respectively, and *n* is the sample size.

### B.2.2 Kendall's correlation coefficient

Kendall's rank correlation coefficient *tau* (Wilcox, 2001) is defined as

$$\tau = \pi_c - \pi_d \tag{B.10}$$

where $\pi_c$ and $\pi_d$ are the probabilities of concordance and discordance respectively. A pair of observations, $(x_1, y_1)$ and $(x_2, y_2)$ shows concordance if $x_1 > x_2$ and $y_1 > y_2$ or $x_1 < x_2$ and $y_1 < y_2$, otherwise the pair shows discordance. The values $\pi_c$ and $\pi_d$ are computed for all possible pairs for a data sample. For a data sample of size *n*, there are $\frac{n(n-1)}{2}$ possible pairs. However, some pairs will be tied i.e. having neither concordance nor discordance.

### B.2.3 Pearson's chi-square statistic

Pearson's chi-square statistic measures the level of association between two qualitative random variables *X* and *Y* (Giudici, 2003). The statistic is computed using the frequencies in a contingency table. A contingency table is a cross-tabulation which gives the frequencies of co-occurrence of the values (levels) of the variables *X* and *Y*. Pearson's chi-square statistic is defined as

$$\chi^2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \frac{(n_{ij} - n^*_{ij})^2}{n^*_{ij}} \tag{B.11}$$

where *I* and *J* are respectively the number of rows and columns in the contingency table, $n_{ij}$ are the observed frequencies in the cells of the contingency table and, $n^*_{ij}$ are the expected frequencies for the cells of the contingency table under the null hypothesis of independence between *X* and *Y*.

The $\phi$ coefficient and Cramer's *V* coefficients are derived from Pearson's chi-square coefficient, and have the same interpretation as Pearson's *r* coefficient. The $\phi$ coefficient is defined as (Giudici, 2003)

$$\phi^2 = \frac{\chi^2}{n} \tag{B.12}$$

and Cramer's $V$ coefficient is defined as

$$v^2 = \frac{\chi^2}{n.\min\{I-1, J-1\}} \tag{B.13}$$

The $\phi$ coefficient, Cramer's $V$ coefficient, and symmetrical uncertainty coefficient can all be used to measure the level of association between two qualitative features.

## B.3 Gini concentration coefficient

Suppose there are *n* entities on which a given property *EP* has been measured yielding *n* pairs of measurement values $\{(1, EP_1),...,(i, EP_i),..,(n, EP_n)\}$ where *i* identifies the $i^{th}$ entity and $EP_i$ identifies the measurement value for the $i^{th}$ entity. Let $F_i$ be the cumulative percentage of the count of entities from the first to the $i^{th}$ entity. Let $Q_i$ be the cumulative percentage of the measurement values from the first measurement, $EP_1$ to the $i^{th}$ measurement, $EP_i$. A summary statistic of the concentration of the measured property *EP* among the *n* entities is called the Gini concentration coefficient defined as

$$Gini = \frac{\sum_{i=1}^{n-1}(F_i - Q_i)}{\sum_{i=1}^{n-1} F_i} \tag{B.14}$$

The *Gini* measure equals 0 for minimum concentration and 1 for maximum concentration. Minimum concentration means that all *n* entities have equal values of the property *EP*. Maximum concentration means that only one entity possesses the property *EP* and all other *n-1* entities have a value of 0 for *EP*.

The Gini concentration coefficient is related to the Area Under the ROC curve (AUC) as follows: The EP property corresponds to the scores that are assigned by a probabilistic classifier. The AUC was discussed in section 4.7.

## B.4 Computation of confidence intervals for the mean

A *P%* confidence interval for the mean is an interval that is expected with probability *P%* to contain the true value of the population mean (Mitchell, 1997). Laplace's estimate of the confidence interval of the population mean is defined as

$$CI = \left( \bar{x} - Z_P \frac{S_X}{\sqrt{n}}, \bar{x} + Z_P \frac{S_X}{\sqrt{n}} \right) \tag{B.15}$$

where $\bar{x}$ is the sample mean for random variable *X*, $S_X$ is the sample standard deviation, and *n* is the sample size (Wilcox, 2001; Mitchell, 1997). Different values of $Z_P$ are used to obtain different confidence intervals. A value of $Z_P = 1.96$ is used for the 95% confidence interval. A value of $Z_P = 2.58$ is used for the 99% confidence interval (Wilcox, 2001; Mitchell, 1997).

# Appendix C

# Descriptive statistics for the datasets

The descriptive statistics for the datasets used in the experiments are presented in this section.

## C.1 Forest cover type dataset

Figure C.1 provides the class frequencies and a graphic representation for the forest cover type dataset classes. Tables C.1 and C.2 show the descriptive statistics for the qualitative and quantitative variables in the forest cover type dataset.

| Class label | Class name | Percent |
|---|---|---|
| 1 | Spruce / fir | 36.5 |
| 2 | Lodgepole pine | 48.8 |
| 3 | Panderosa pine | 6.2 |
| 4 | Cottonwood / Willow | .5 |
| 5 | Aspen | 1.6 |
| 6 | Douglas-fir | 3.0 |
| 7 | Krummholz | 3.5 |

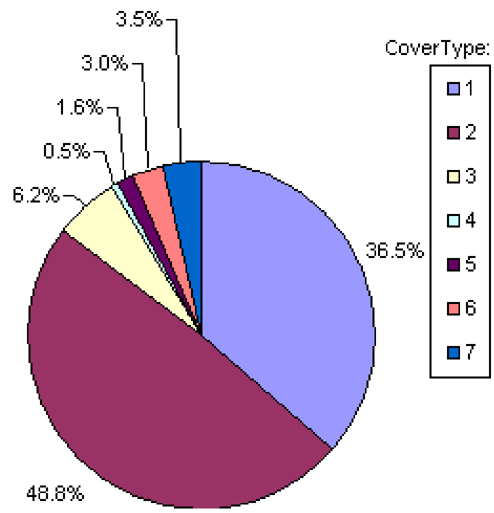


*Figure C.1: Class frequencies for the forest cover type class variable (covertype)*

*Table C.1: Descriptive statistics for the quantitative variables in the forest cover type dataset*

| | Minimum | Maximum | Mean | Standard Deviation | Coefficient of variation (CV) |
|---|---|---|---|---|---|
| Aspect | 0 | 360 | 155.7 | 111.9 | 0.7 |
| Elevation | 1859 | 3858 | 2959.4 | 280.0 | 0.1 |
| Slope | 0 | 66 | 14.1 | 7.5 | 0.5 |
| HorizDistToHydro | 0 | 1397 | 269.4 | 212.5 | 0.8 |
| VertDistToHydro | -173 | 601 | 46.4 | 58.3 | 1.3 |
| HorizDistToRoad | 0 | 7117 | 2350.2 | 1559.3 | 0.7 |
| HillShade9am | 0 | 254 | 212.2 | 26.8 | 0.1 |
| HillShadeNoon | 0 | 254 | 223.3 | 19.8 | 0.1 |
| HillShade3pm | 0 | 254 | 142.5 | 38.3 | 0.3 |
| HorizDistToFire | 0 | 7173 | 1980.3 | 1324.2 | 0.7 |

*Table C.2: Descriptive statistics for the qualitative variables for the forest cover type dataset*

| Variable name | Percentage for '0' | Percentage for '1' | Variable name | Percentage for '0' | Percentage for '1' |
|---|---|---|---|---|---|
| WildernessArea1 | 55.1 | 44.9 | SoilType19 | 99.3 | 0.7 |
| WildernessArea2 | 94.9 | 5.1 | SoilType20 | 98.4 | 1.6 |
| WildernessArea3 | 56.4 | 43.6 | SoilType21 | 99.9 | 0.1 |
| WildernessArea4 | 93.6 | 6.4 | SoilType22 | 94.3 | 5.7 |
| SoilType1 | 99.5 | 0.5 | SoilType23 | 90.1 | 9.9 |
| SoilType2 | 98.7 | 1.3 | SoilType24 | 96.3 | 3.7 |
| SoilType3 | 99.2 | 0.8 | SoilType25 | 99.9 | 0.1 |
| SoilType4 | 97.9 | 2.1 | SoilType26 | 99.6 | 0.4 |
| SoilType5 | 99.7 | 0.3 | SoilType27 | 99.8 | 0.2 |
| SoilType6 | 98.9 | 1.1 | SoilType28 | 99.8 | 0.2 |
| SoilType7 | 99.98 | 0.02 | SoilType29 | 80.2 | 19.8 |
| SoilType8 | 99.97 | 0.03 | SoilType30 | 94.8 | 5.2 |
| SoilType9 | 99.8 | 0.2 | SoilType31 | 95.6 | 4.4 |
| SoilType10 | 94.4 | 5.6 | SoilType32 | 91 | 9 |
| SoilType11 | 97.9 | 2.1 | SoilType33 | 92.2 | 7.8 |
| SoilType12 | 94.8 | 5.2 | SoilType34 | 99.7 | 0.3 |
| SoilType13 | 97 | 3 | SoilType35 | 99.7 | 0.3 |
| SoilType14 | 99.9 | 0.1 | SoilType36 | 100 | 0 |
| SoilType15 | 100 | 0 | SoilType37 | 99.9 | 0.1 |
| SoilType16 | 99.5 | 0.5 | SoilType38 | 97.3 | 2.7 |
| SoilType17 | 99.4 | 0.6 | SoilType39 | 97.6 | 2.4 |
| SoilType18 | 99.7 | 0.3 | SoilType40 | 98.5 | 1.5 |

## C.2 KDD Cup 1999 dataset

Figure C.2 provides the class frequencies and a graphic representation for the KDD Cup 1999 dataset classes. Tables C.3 and C.4 give the descriptive statistics for the variables in the KDD Cup 1999 dataset.

| Class | Frequency | Percent |
|---|---|---|
| DOS | 10851 | 20.9 |
| NORMAL | 35794 | 68.9 |
| PROBE | 4107 | 7.9 |
| R2L | 1126 | 2.2 |
| U2R | 52 | 0.1 |
| Total | 51930 | 100.0 |

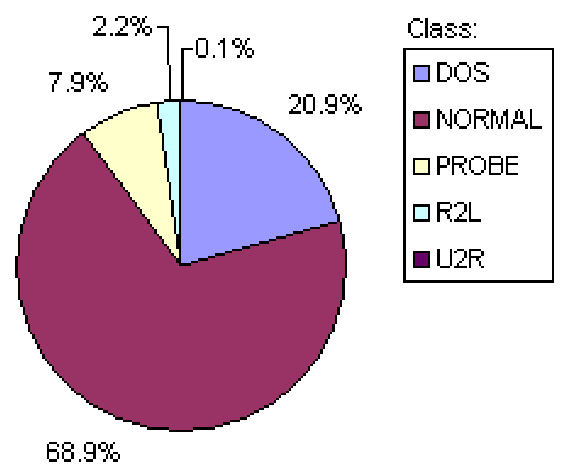


*Figure C.2: Class frequencies for the KDD Cup 1999 training dataset derived class variable (class)*

*Table C.3: Descriptive statistics for the quantitative variables for the KDD Cup 1999 training dataset*

| Variable name | Minimum | Maximum | Mean | Standard Deviation | Coefficient of variation (CV) |
|---|---|---|---|---|---|
| Counted | 0 | 511 | 53.3 | 120.4 | 2.3 |
| DiffSrvRate | 0 | 1 | 0.1 | 0.2 | 2.0 |
| DstBytes | 0 | 5,155,468.00 | 3,758.50 | 99,612.90 | 26.5 |
| DstHostCount | 1 | 255 | 191 | 93.2 | 0.5 |
| DstHostDiffSrvRate | 0 | 1 | 0.2 | 0.3 | 1.5 |
| DstHostRerrorRate | 0 | 1 | 0.1 | 0.2 | 2.0 |
| DstHostSameSrcPortRate | 0 | 1 | 0.3 | 0.4 | 1.3 |
| DstHostSameSrvRate | 0 | 1 | 0.6 | 0.4 | 0.7 |
| DstHostSerrorRate | 0 | 1 | 0.1 | 0.3 | 3.0 |
| DstHostSrvCount | 1 | 255 | 120.9 | 107.3 | 0.9 |
| DstHostSrvDiffHostRate | 0 | 1 | 0 | 0.1 | undefined |
| DstHostSrvRerrorRate | 0 | 1 | 0.1 | 0.2 | 2.0 |
| DstHostSrvSerrorRate | 0 | 1 | 0.1 | 0.3 | 3.0 |
| Duration | 0 | 58,329.00 | 455.5 | 2,140.00 | 4.7 |
| Hot | 0 | 30 | 0.3 | 2.4 | 8.0 |
| NumAccessFiles | 0 | 8 | 0 | 0.1 | undefined |
| NumCompromised | 0 | 884 | 0.1 | 5.5 | 55.0 |
| NumFailedLogins | 0 | 5 | 0 | 0 | undefined |
| NumFileCreations | 0 | 28 | 0 | 0.3 | undefined |
| NumOutboundCmds | 0 | 0 | 0 | 0 | undefined |
| NumRoot | 0 | 993 | 0.1 | 6.2 | 62.0 |
| NumShells | 0 | 2 | 0 | 0 | undefined |
| RerrorRate | 0 | 1 | 0.1 | 0.2 | 2.0 |
| RootShell | 0 | 1 | 0 | 0 | undefined |
| SameSrvRate | 0 | 1 | 0.8 | 0.4 | 0.5 |
| SerrorRate | 0 | 1 | 0.1 | 0.3 | 3.0 |
| SrcBytes | 0 | 693,000,000.00 | 23,327.40 | 3,047,960.00 | 130.7 |
| SrvCount | 0 | 511 | 20 | 73.9 | 3.7 |
| SrvDiffHostRate | 0 | 1 | 0.1 | 0.3 | 3.0 |
| SrvRerrorRate | 0 | 1 | 0.1 | 0.3 | 3.0 |
| SrvSerrorRate | 0 | 1 | 0.1 | 0.3 | 3.0 |
| SUAttempted | 0 | 2 | 0 | 0 | undefined |
| Urgent | 0 | 3 | 0 | 0 | undefined |
| WrongFragment | 0 | 3 | 0.1 | 0.4 | 4.0 |

*Table C.4: Descriptive statistics for the qualitative variables for the KDD Cup 1999 training dataset*

| Variable | Level description | Level names | Frequency% |
|---|---|---|---|
| ProtocolType | 3 levels | icmp | 7.3 |
| | | tcp | 53.5 |
| | | udp | 39.2 |
| Service | 64 levels | domain_u | 11.3 |
| | | ftp_data | 9.1 |
| | | http | 14.3 |
| | | private | 19.4 |
| | | smtp | 9.9 |
| | | all other services | 36 |
| Flag | 9 levels | SF | 82.1 |
| | | S0 | 10.7 |
| | | all other flags | 7.2 |
| Land | 2 levels | 0 | 99.96 |
| | | 1 | 0.04 |
| LoggedIn | 2 levels | 0 | 67 |
| | | 1 | 33 |
| IsHostLogin | 2 levels | 0 | 100 |
| | | 1 | 0 |
| IsGuestLogin | 2 levels | 0 | 98.7 |
| | | 1 | 1.3 |

## C.3 Abalone3C dataset

Figure C.3 provides the class frequencies and graphic representation for the abalone3C dataset classes. Table C.5 gives the descriptive statistics for the variables.

| Class | Frequency | Percentage |
|---|---|---|
| young | 1407 | 33.7 |
| middle | 1447 | 34.6 |
| old | 1323 | 31.7 |
| Total | 4177 | 100.0 |

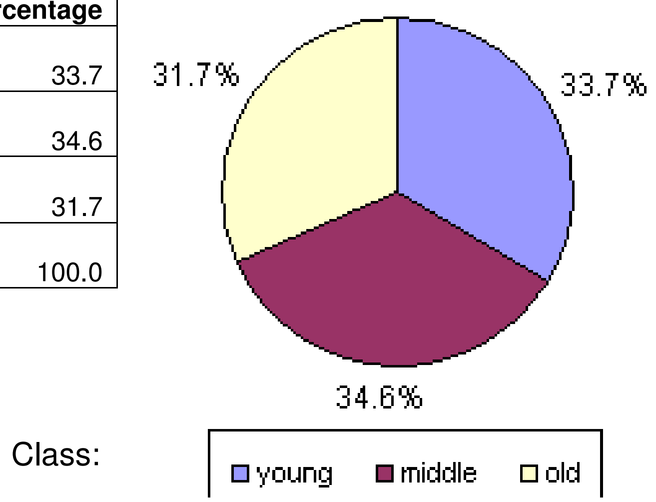


*Figure C.3: Class frequencies for the abalone3C class variable (age)*

*Table C.5: Descriptive statistics for the quantitative variables of abalone3C*

| Variable | Minimum | Maximum | Mean | Standard Deviation | Coefficient of variation (CV) |
|---|---|---|---|---|---|
| Length | 15.0 | 163.0 | 104.8 | 24.0 | 0.2 |
| Diameter | 11.0 | 130.0 | 81.6 | 19.8 | 0.2 |
| Height | 0.0 | 226.0 | 27.9 | 8.4 | 0.3 |
| WholeWeight | 0.4 | 565.1 | 165.7 | 98.1 | 0.6 |
| ShuckledWeight | 0.2 | 297.6 | 71.9 | 44.4 | 0.6 |
| VisceraWeight | 0.1 | 152.0 | 36.1 | 21.9 | 0.6 |
| ShellWeight | 0.3 | 201.0 | 47.8 | 27.8 | 0.6 |

The qualitative variable gender has three levels with absolute frequencies of: 1528 for male (M), 1307 for female (F) and 1342 for infant (I).

## C.4 Wine quality datasets

Figure C.4 provides the class frequencies and graphic representation for the wine quality (white) dataset classes. The two minority classes: 3 (20 instances) and 9 (5 instances) were removed from the dataset. Table C.6 gives the descriptive statistics for the variables.

| Class | Frequency | Percentage |
|---|---|---|
| 4 | 163 | 3.3 |
| 5 | 1457 | 29.9 |
| 6 | 2198 | 45.1 |
| 7 | 880 | 18.1 |
| 8 | 175 | 3.6 |
| Total | 4873 | 100.0 |

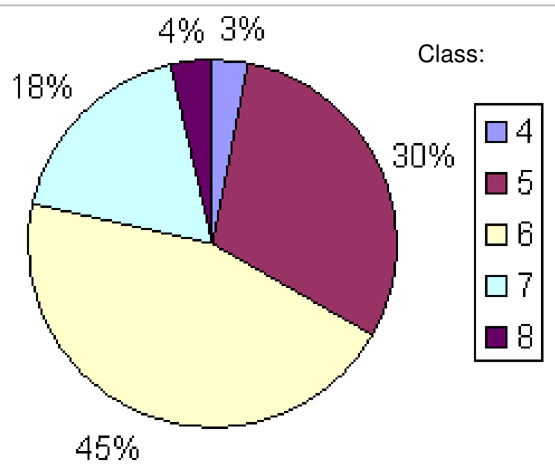


*Figure C.4: Class frequencies for the wine quality (white) class variable (quality)*

*Table C.6 Descriptive statistics for the Wine quality (white) dataset variables*

| Variable | Minimum | Maximum | Mean | Standard Deviation | Coeff of variation (CV) |
|---|---|---|---|---|---|
| FixedAcidity | 3.8 | 14.2 | 6.9 | 0.8 | 0.1 |
| VolatileAcidity | 0.1 | 1.1 | 0.3 | 0.1 | 0.4 |
| CitricAcid | 0.0 | 1.7 | 0.3 | 0.1 | 0.4 |
| ResidualSugar | 0.6 | 65.8 | 6.4 | 5.1 | 0.8 |
| Chlorides | 0.0 | 0.3 | 0.0 | 0.0 | 0.5 |
| FreeSulfurDioxide | 2.0 | 289.0 | 35.3 | 17.0 | 0.5 |
| TotalSulfurDioxide | 9.0 | 440.0 | 138.4 | 42.5 | 0.3 |
| Density | 1.0 | 1.0 | 1.0 | 0.0 | 0.0 |
| pH | 2.7 | 3.8 | 3.2 | 0.2 | 0.0 |
| Sulphates | 0.2 | 1.1 | 0.5 | 0.1 | 0.2 |
| Alcohol | 8.0 | 14.2 | 10.5 | 1.2 | 0.1 |

## C.5 Mushroom dataset

Table C.7 gives the descriptive statistics for the mushroom dataset. The variables for this dataset are all qualitative nominal.

*Table C.8 Descriptive statistics for the mushroom dataset variables*

| Variable | Level description | Level name | Frequ-ency% | Variable | Level description | Level name | Frequ-ency% |
|---|---|---|---|---|---|---|---|
| CapShape | 6 levels | FLAT | 39.1 | StalkRoot | 5 levels | EQUAL | 16.3 |
| | | CONVEX | 45.1 | | | BULBOUS | 45.2 |
| | | All other | 15.8 | | | UNKNOWN | 29.5 |
| CapSurface | 4 levels | GROOVES | 0.05 | | | All other | 9.0 |
| | | SMOOTH | 31.9 | StalkSfAbvRing | 4 levels | SILKY | 28.3 |
| | | FIBROUS | 29.2 | | | SMOOTH | 63.2 |
| | | SCALY | 38.8 | | | All other | 8.5 |
| CapColor | 10 levels | WHITE | 12.4 | StalkSfBlRing | 4 levels | SILKY | 27.4 |
| | | RED | 17.8 | | | SMOOTH | 60.3 |
| | | YELLOW | 12.7 | | | All other | 12.3 |
| | | BROWN | 27.6 | StalkClAbvRing | 9 levels | WHITE | 56.4 |
| | | GRAY | 24.9 | | | PINK | 22.2 |
| | | All other | 4.6 | | | All other | 21.4 |
| Bruises? | 2 levels | NO | 59.9 | StalkClBlRing | 9 levels | WHITE | 55.1 |
| | | BRUISES | 40.1 | | | PINK | 22.2 |
| Odor | 9 levels | FOUL | 25.7 | | | All other | 22.6 |
| | | NONE | 45.2 | VeilType | 1 level | PARTIAL | 100.0 |
| | | All other | 29.1 | VeilColor | 4 levels | WHITE | 97.6 |
| GillAttach | 2 levels | FREE | 97.4 | | | All other | 2.4 |
| | | ATTACHED | 2.6 | RingNumber | 3 levels | ONE | 92.3 |
| GillSpace | 2 levels | CROWDED | 18.9 | | | All other | 7.7 |
| | | CLOSE | 81.1 | RingType | 5 levels | LARGE | 15.4 |
| GillSize | 2 levels | NARROW | 30.1 | | | PENDANT | 47.1 |
| | | BROAD | 69.9 | | | EVANESCENT | 36.3 |
| GillColor | 12 levels | WHITE | 14.6 | | | All other | 1.1 |
| | | PINK | 18.5 | SporePrintColor | 9 levels | BLACK | 23.8 |
| | | BUFF | 20.5 | | | WHITE | 28.8 |
| | | BROWN | 13.2 | | | CHOCOLATE | 19.4 |
| | | All other | 33.1 | | | BROWN | 24.9 |
| | | GRAY | 8.9 | | | All other | 3.1 |
| StalkShape | 2 levels | ENLARGING | 42.2 | Population | 6 levels | SOLITARY | 20.3 |
| | | TAPERING | 57.8 | | | SEVERAL | 48.3 |
| Habitat | 7 levels | PATHS | 13.6 | | | SCATTERED | 16.3 |
| | | LEAVES | 10.2 | | | All other | 15.0 |
| | | GRASSES | 28.6 | **Class** | **2 levels** | **EDIBLE** | **53.3** |
| | | WOODS | 37.5 | | | **POISONOUS** | **46.7** |
| | | All other | 10.1 | | | | |

# Appendix D

# Correlation measurements for feature selection

The details of feature selection discussed in chapters 5 and 7 are presented in this appendix. Tables D.1 to D.4 show the class-feature correlations and the number of features selected by the t-test and the probes using Pearson's r and Kendall's tau measures of correlation for the forest cover type dataset.

*Table D.1: Feature selection for Forest cover type*

| Sample size for correlation measurement | Selection criteria (Number of selected features) | Top 10 features | | | | |
|---|---|---|---|---|---|---|
| | | Feature | Mean $Corr_{cf}$ | StDev | 95% CI of mean Low | High |
| 100 | **Pearson's r** t-test (3) | WildernessArea4 | 0.2 | 0.06 | 0.16 | 0.24 |
| | | SoilType38 | 0.14 | 0.04 | 0.12 | 0.16 |
| | | Elevation | 0.14 | 0.04 | 0.12 | 0.16 |
| 500 and 1000 | Pearson's r t-test (6) (WildernessArea1 is selected for sample size 500, SoilType10 is selected for size 1000) | WildernessArea4 | 0.22 | 0.02 | 0.21 | 0.23 |
| | | SoilType12 | 0.16 | 0.02 | 0.15 | 0.17 |
| | | SoilType22 | 0.14 | 0.03 | 0.12 | 0.16 |
| | | Elevation | 0.13 | 0.02 | 0.12 | 0.14 |
| | | WildernessArea1 | 0.12 | 0.01 | 0.11 | 0.13 |
| | | SoilType38 | 0.12 | 0.02 | 0.11 | 0.13 |
| 100 | **Kendall's tau:** t-test (20) Uniform probe (26) Uniform binary probe (21) Gaussian probe (31) | WildernessArea4 | 0.58 | 0.15 | 0.49 | 0.67 |
| | | SoilType12 | 0.51 | 0.19 | 0.39 | 0.63 |
| | | SoilType38 | 0.44 | 0.1 | 0.38 | 0.50 |
| | | SoilType22 | 0.43 | 0.17 | 0.32 | 0.54 |
| | | SoilType10 | 0.4 | 0.13 | 0.32 | 0.48 |
| | | SoilType39 | 0.38 | 0.17 | 0.27 | 0.49 |
| | | SoilType4 | 0.35 | 0.2 | 0.23 | 0.47 |
| | | SoilType23 | 0.35 | 0.15 | 0.26 | 0.44 |
| | | SoilType11 | 0.32 | 0.16 | 0.22 | 0.42 |
| | | SoilType30 | 0.31 | 0.19 | 0.19 | 0.43 |
| 500 | **Kendall's tau** t-test (35) Uniform probe (47) Uniform binary probe (44) Gaussian probe (47) | WildernessArea4 | 0.81 | 0.03 | 0.79 | 0.83 |
| | | SoilType12 | 0.72 | 0.08 | 0.67 | 0.77 |
| | | SoilType38 | 0.6 | 0.08 | 0.55 | 0.65 |
| | | SoilType39 | 0.58 | 0.09 | 0.52 | 0.64 |
| | | SoilType2 | 0.58 | 0.15 | 0.49 | 0.67 |
| | | SoilType22 | 0.57 | 0.1 | 0.51 | 0.63 |
| | | SoilType4 | 0.57 | 0.12 | 0.50 | 0.64 |
| | | SoilType6 | 0.56 | 0.11 | 0.49 | 0.63 |
| | | SoilType13 | 0.56 | 0.11 | 0.49 | 0.63 |
| | | SoilType40 | 0.48 | 0.11 | 0.41 | 0.55 |
| 1000 | **Kendall's tau:** t-test (38) Uniform probe (48) Uniform binary probe (47) Gaussian probe (49) | WildernessArea4 | 0.86 | 0.02 | 0.85 | 0.87 |
| | | SoilType12 | 0.7 | 0.07 | 0.66 | 0.74 |
| | | SoilType1 | 0.69 | 0.05 | 0.66 | 0.72 |
| | | SoilType38 | 0.68 | 0.08 | 0.63 | 0.73 |
| | | SoilType39 | 0.68 | 0.08 | 0.63 | 0.73 |
| | | SoilType2 | 0.64 | 0.1 | 0.58 | 0.70 |
| | | SoilType4 | 0.64 | 0.05 | 0.61 | 0.67 |
| | | SoilType6 | 0.6 | 0.1 | 0.54 | 0.66 |
| | | SoilType22 | 0.59 | 0.1 | 0.53 | 0.65 |
| | | SoilType10 | 0.58 | 0.05 | 0.55 | 0.61 |

*Table D.2: Feature selection for forest cover type using Kendall's tau and a Gaussian probe*

| Rank | Feature | Kendall's tau | | Feature 95% CI | | Gaussian probe 95% CI | | Select |
|---|---|---|---|---|---|---|---|---|
| | | Mean | Stdev | Low | High | Low | High | |
| 1 | WildernessArea4 | 0.86 | 0.02 | 0.84 | 0.87 | 0.02 | 0.05 | yes |
| 2 | SoilType12 | 0.70 | 0.07 | 0.66 | 0.75 | 0.02 | 0.05 | yes |
| 3 | SoilType1 | 0.69 | 0.05 | 0.65 | 0.72 | 0.02 | 0.05 | yes |
| 4 | SoilType38 | 0.68 | 0.08 | 0.63 | 0.73 | 0.02 | 0.05 | yes |
| 5 | SoilType39 | 0.68 | 0.08 | 0.62 | 0.73 | 0.02 | 0.05 | yes |
| 6 | SoilType2 | 0.64 | 0.10 | 0.58 | 0.70 | 0.02 | 0.05 | yes |
| 7 | SoilType4 | 0.64 | 0.05 | 0.61 | 0.67 | 0.02 | 0.05 | yes |
| 8 | SoilType6 | 0.60 | 0.10 | 0.54 | 0.67 | 0.02 | 0.05 | yes |
| 9 | SoilType22 | 0.59 | 0.10 | 0.53 | 0.65 | 0.02 | 0.05 | yes |
| 10 | SoilType10 | 0.58 | 0.05 | 0.55 | 0.61 | 0.02 | 0.05 | yes |
| 11 | SoilType3 | 0.55 | 0.10 | 0.48 | 0.61 | 0.02 | 0.05 | yes |
| 12 | SoilType40 | 0.55 | 0.10 | 0.49 | 0.61 | 0.02 | 0.05 | yes |
| 13 | SoilType13 | 0.53 | 0.10 | 0.47 | 0.59 | 0.02 | 0.05 | yes |
| 14 | SoilType11 | 0.48 | 0.08 | 0.43 | 0.52 | 0.02 | 0.05 | yes |
| 15 | SoilType35 | 0.44 | 0.09 | 0.39 | 0.50 | 0.02 | 0.05 | yes |
| 16 | SoilType18 | 0.44 | 0.17 | 0.34 | 0.54 | 0.02 | 0.05 | yes |
| 17 | SoilType17 | 0.43 | 0.16 | 0.34 | 0.53 | 0.02 | 0.05 | yes |
| 18 | SoilType26 | 0.43 | 0.16 | 0.33 | 0.53 | 0.02 | 0.05 | yes |
| 19 | SoilType34 | 0.40 | 0.18 | 0.29 | 0.51 | 0.02 | 0.05 | yes |
| 20 | SoilType23 | 0.40 | 0.04 | 0.37 | 0.43 | 0.02 | 0.05 | yes |
| 21 | WildernessArea2 | 0.39 | 0.12 | 0.31 | 0.47 | 0.02 | 0.05 | yes |
| 22 | SoilType5 | 0.36 | 0.22 | 0.22 | 0.50 | 0.02 | 0.05 | yes |
| 23 | SoilType19 | 0.35 | 0.17 | 0.25 | 0.46 | 0.02 | 0.05 | yes |
| 24 | SoilType30 | 0.34 | 0.10 | 0.28 | 0.40 | 0.02 | 0.05 | yes |
| 25 | SoilType16 | 0.33 | 0.13 | 0.25 | 0.41 | 0.02 | 0.05 | yes |
| 26 | SoilType21 | 0.32 | 0.20 | 0.20 | 0.44 | 0.02 | 0.05 | yes |
| 27 | SoilType29 | 0.30 | 0.04 | 0.27 | 0.32 | 0.02 | 0.05 | yes |
| 28 | WildernessArea1 | 0.28 | 0.03 | 0.27 | 0.30 | 0.02 | 0.05 | yes |
| 29 | SoilType9 | 0.28 | 0.16 | 0.19 | 0.38 | 0.02 | 0.05 | yes |
| 30 | Elevation | 0.28 | 0.01 | 0.27 | 0.29 | 0.02 | 0.05 | yes |
| 31 | SoilType24 | 0.26 | 0.09 | 0.20 | 0.32 | 0.02 | 0.05 | yes |
| 32 | SoilType14 | 0.23 | 0.22 | 0.10 | 0.37 | 0.02 | 0.05 | yes |
| 33 | SoilType31 | 0.22 | 0.08 | 0.17 | 0.27 | 0.02 | 0.05 | yes |
| 34 | SoilType28 | 0.21 | 0.15 | 0.12 | 0.31 | 0.02 | 0.05 | yes |
| 35 | SoilType32 | 0.21 | 0.02 | 0.19 | 0.22 | 0.02 | 0.05 | yes |
| 36 | SoilType33 | 0.18 | 0.04 | 0.16 | 0.21 | 0.02 | 0.05 | yes |
| 37 | SoilType8 | 0.18 | 0.16 | 0.08 | 0.27 | 0.02 | 0.05 | yes |
| 38 | SoilType20 | 0.16 | 0.03 | 0.14 | 0.18 | 0.02 | 0.05 | yes |
| 39 | HorizDistToRoad | 0.16 | 0.01 | 0.15 | 0.17 | 0.02 | 0.05 | yes |
| 40 | HorizDistToFire | 0.16 | 0.01 | 0.15 | 0.16 | 0.02 | 0.05 | yes |
| 41 | SoilType27 | 0.15 | 0.15 | 0.05 | 0.24 | 0.02 | 0.05 | yes |
| 42 | Slope | 0.12 | 0.02 | 0.11 | 0.14 | 0.02 | 0.05 | yes |
| 43 | HillShade9am | 0.08 | 0.02 | 0.07 | 0.10 | 0.02 | 0.05 | yes |
| 44 | VertDistToHydro | 0.07 | 0.02 | 0.06 | 0.08 | 0.02 | 0.05 | yes |
| 45 | HorizDistToHydro | 0.07 | 0.02 | 0.06 | 0.08 | 0.02 | 0.05 | yes |
| 46 | WildernessArea3 | 0.07 | 0.03 | 0.05 | 0.09 | 0.02 | 0.05 | yes |
| 47 | HillShadeNoon | 0.07 | 0.02 | 0.06 | 0.08 | 0.02 | 0.05 | yes |
| 48 | Aspect | 0.05 | 0.02 | 0.03 | 0.06 | 0.02 | 0.05 | yes |
| 49 | HillShade3pm | 0.04 | 0.02 | 0.03 | 0.06 | 0.02 | 0.05 | yes |
| **50** | **Probe1GaussCont** | **0.04** | **0.02** | **0.02** | **0.05** | **0.02** | **0.05** | **no** |

Tables D.4 and D.5 show the class-feature correlations using Pearson's r, Kendall's tau and SU coefficient, and the number of features selected by the t-test, probes and decision rule-based algorithm for the KDDCup 1999 dataset.

*Table D.3 Features selected by the decision rule-based search algorithm for different inputs*

| Input feature set selected by: | Number of selected features | | Top 10 features for all methods | |
|---|---|---|---|---|
| | | | Feature | mean $corr_{cf}$ |
| No pre-selection (54 features + 3 probes) | 42 | | WildernessArea4 | 0.855 |
| | | | SoilType2 | 0.642 |
| Gaussian probe (49 features) | 41 | | SoilType40 | 0.547 |
| | | | SoilType38 | 0.676 |
| Uniform probe (48 features) | 41 | | SoilType4 | 0.638 |
| | | | SoilType1 | 0.686 |
| Uniform binary probe (47 features) | 41 | | SoilType3 | 0.548 |
| | | | SoilType6 | 0.603 |
| t-test for means (36 features) | 36 | | SoilType13 | 0.527 |
| | | | SoilType39 | 0.676 |

*Table D.4: Feature selection for KDD Cup 1999*

| Sample size for correlation measurement | Selection criteria (Number of selected features) | Top 10 features | | | 95% CI of mean | |
|---|---|---|---|---|---|---|
| | | Feature | Mean $Corr_{cf}$ | StDev | Low | High |
| 1000 | Pearson's r: t-test (21) Uniform probe (32) Uniform binary probe (31) Gaussian probe (31) | SameSrvRate | 0.53 | 0.02 | 0.52 | 0.54 |
| | | SerrorRate | 0.51 | 0.02 | 0.50 | 0.52 |
| | | DstHostSerrorRate | 0.51 | 0.02 | 0.50 | 0.52 |
| | | Counted | 0.51 | 0.02 | 0.50 | 0.52 |
| | | SrvSerrorRate | 0.50 | 0.02 | 0.49 | 0.51 |
| | | DstHostSrvSerrorRate | 0.50 | 0.02 | 0.49 | 0.51 |
| | | Flag | 0.43 | 0.02 | 0.42 | 0.44 |
| | | DstHostRerrorRate | 0.36 | 0.03 | 0.34 | 0.38 |
| | | SrvRerrorRate | 0.35 | 0.03 | 0.33 | 0.37 |
| | | RerrorRate | 0.34 | 0.03 | 0.32 | 0.36 |
| 500 | Kendall's tau: t-test (34) Uniform probe (36) Uniform binary probe (36) Gaussian probe (36) | SrvSerrorRate | 0.90 | 0.02 | 0.89 | 0.91 |
| | | SerrorRate | 0.87 | 0.02 | 0.86 | 0.88 |
| | | NumCompromised | 0.85 | 0.03 | 0.83 | 0.87 |
| | | DstHostSrvSerrorRate | 0.83 | 0.04 | 0.81 | 0.85 |
| | | WrongFragment | 0.81 | 0.04 | 0.78 | 0.84 |
| | | DstHostSerrorRate | 0.81 | 0.02 | 0.80 | 0.82 |
| | | SrvRerrorRate | 0.80 | 0.04 | 0.78 | 0.82 |
| | | Hot | 0.78 | 0.04 | 0.76 | 0.80 |
| | | DstHostSrvRerrorRate | 0.76 | 0.05 | 0.73 | 0.79 |
| | | RerrorRate | 0.76 | 0.05 | 0.73 | 0.79 |
| 1000 | Kendall's tau: t-test (30) Uniform probe (36) Uniform binary probe (35) Gaussian probe (36) | SerrorRate | 0.92 | 0.01 | 0.91 | 0.93 |
| | | NumCompromised | 0.92 | 0.03 | 0.90 | 0.94 |
| | | SrvSerrorRate | 0.91 | 0.01 | 0.90 | 0.92 |
| | | WrongFragment | 0.9 | 0.01 | 0.89 | 0.91 |
| | | DstHostSrvSerrorRate | 0.85 | 0.01 | 0.84 | 0.86 |
| | | DstHostSrvRerrorRate | 0.85 | 0.01 | 0.84 | 0.86 |
| | | SrvRerrorRate | 0.85 | 0.02 | 0.84 | 0.86 |
| | | Hot | 0.84 | 0.03 | 0.82 | 0.86 |
| | | DstHostSerrorRate | 0.84 | 0.02 | 0.83 | 0.85 |
| | | RerrorRate | 0.82 | 0.03 | 0.80 | 0.84 |

*Table D.5: Feature selection for KDD Cup1999 using  Kendall's tau and the Gaussian probe*

| Rank | Feature | **Mean** | **StDev** | Feature 95% CI | | Gauss probe 95% CI | | Select |
|---|---|---|---|---|---|---|---|---|
| | | | | **Low** | **High** | **Low** | **High** | |
| 1 | SerrorRate | 0.92 | 0.01 | 0.91 | 0.92 | 0.02 | 0.04 | yes |
| 2 | NumCompromised | 0.92 | 0.03 | 0.90 | 0.93 | 0.02 | 0.04 | yes |
| 3 | SrvSerrorRate | 0.91 | 0.01 | 0.91 | 0.92 | 0.02 | 0.04 | yes |
| 4 | WrongFragment | 0.90 | 0.01 | 0.89 | 0.91 | 0.02 | 0.04 | yes |
| 5 | DstHostSrvSerrorRate | 0.85 | 0.01 | 0.85 | 0.86 | 0.02 | 0.04 | yes |
| 6 | DstHostSrvRerrorRate | 0.85 | 0.01 | 0.84 | 0.85 | 0.02 | 0.04 | yes |
| 7 | SrvRerrorRate | 0.85 | 0.02 | 0.83 | 0.86 | 0.02 | 0.04 | yes |
| 8 | Hot | 0.84 | 0.03 | 0.83 | 0.86 | 0.02 | 0.04 | yes |
| 9 | DstHostSerrorRate | 0.84 | 0.02 | 0.82 | 0.85 | 0.02 | 0.04 | yes |
| 10 | RerrorRate | 0.82 | 0.03 | 0.80 | 0.84 | 0.02 | 0.04 | yes |
| 11 | SameSrvRate | 0.82 | 0.01 | 0.81 | 0.83 | 0.02 | 0.04 | yes |
| 12 | DstHostRerrorRate | 0.80 | 0.03 | 0.79 | 0.82 | 0.02 | 0.04 | yes |
| 13 | DiffSrvRate | 0.73 | 0.02 | 0.71 | 0.74 | 0.02 | 0.04 | yes |
| 14 | NumRoot | 0.68 | 0.10 | 0.62 | 0.74 | 0.02 | 0.04 | yes |
| 15 | Counted | 0.63 | 0.01 | 0.62 | 0.64 | 0.02 | 0.04 | yes |
| 16 | DstBytes | 0.58 | 0.06 | 0.55 | 0.62 | 0.02 | 0.04 | yes |
| 17 | SrcBytes | 0.49 | 0.05 | 0.46 | 0.52 | 0.02 | 0.04 | yes |
| 18 | SrvDiffHostRate | 0.46 | 0.08 | 0.41 | 0.50 | 0.02 | 0.04 | yes |
| 19 | DstHostSrvDiffHostRate | 0.44 | 0.05 | 0.41 | 0.47 | 0.02 | 0.04 | yes |
| 20 | Flag | 0.43 | 0.02 | 0.41 | 0.44 | 0.02 | 0.04 | yes |
| 21 | SrvCount | 0.42 | 0.02 | 0.41 | 0.44 | 0.02 | 0.04 | yes |
| 22 | DstHostCount | 0.37 | 0.03 | 0.35 | 0.39 | 0.02 | 0.04 | yes |
| 23 | DstHostSrvCount | 0.31 | 0.04 | 0.29 | 0.34 | 0.02 | 0.04 | yes |
| 24 | NumFailedLogins | 0.30 | 0.23 | 0.16 | 0.44 | 0.02 | 0.04 | yes |
| 25 | NumFileCreations | 0.30 | 0.08 | 0.25 | 0.35 | 0.02 | 0.04 | yes |
| 26 | DstHostSameSrcPortRate | 0.28 | 0.05 | 0.25 | 0.31 | 0.02 | 0.04 | yes |
| 27 | Duration | 0.25 | 0.02 | 0.24 | 0.27 | 0.02 | 0.04 | yes |
| 28 | Service | 0.24 | 0.01 | 0.23 | 0.24 | 0.02 | 0.04 | yes |
| 29 | DstHostSameSrvRate | 0.22 | 0.04 | 0.20 | 0.25 | 0.02 | 0.04 | yes |
| 30 | NumShells | 0.20 | 0.16 | 0.11 | 0.30 | 0.02 | 0.04 | yes |
| 31 | NumAccessFiles | 0.18 | 0.20 | 0.06 | 0.30 | 0.02 | 0.04 | yes |
| 32 | ProtocolType | 0.15 | 0.02 | 0.14 | 0.16 | 0.02 | 0.04 | yes |
| 33 | DstHostDiffSrvRate | 0.14 | 0.04 | 0.12 | 0.17 | 0.02 | 0.04 | yes |
| 34 | RootShell | 0.11 | 0.15 | 0.02 | 0.20 | 0.02 | 0.04 | no |
| 35 | LoggedIn | 0.08 | 0.01 | 0.08 | 0.09 | 0.02 | 0.04 | yes |
| 36 | IsGuestLogin | 0.04 | 0.01 | 0.03 | 0.05 | 0.02 | 0.04 | yes |
| 37 | Urgent | 0.03 | 0.11 | -0.03 | 0.10 | 0.02 | 0.04 | no |
| **38** | **Probe1GaussCont** | **0.03** | **0.02** | **0.02** | **0.04** | **0.02** | **0.04** | **no** |

Tables D.7 and D.9 show the class-feature correlations using Pearson's r, Kendall's tau and the SU coefficient, and the number of features selected by the t-test, probes and decision rule-based algorithm for the abalone3C and mushroom datasets. Table D.8 shows the feature-feature correlations for abalone3C.

*Table D.6: KDD Cup 1999 feature selection by decision rule*

| Input feature set selected by: | Number of selected features |
|---|---|
| No pre-selection (41 features + 3 probes) | 32 |
| Gaussian probe (36 features) | 34 |
| Uniform probe (36 features) | 34 |
| Uniform binary probe (35 features) | 34 |
| t-test for means (30 features) | 30 |

| Top 10 for no-preselection (32 features selected) | |
|---|---|
| Feature | mean $corr_{cf}$ |
| SerrorRate | 0.92 |
| DstHostRerrorRate | 0.81 |
| NumRoot | 0.68 |
| WrongFragment | 0.90 |
| Flag | 0.43 |
| NumFailedLogins | 0.30 |
| DstHostSerrorRate | 0.84 |
| DstHostSrvCount | 0.31 |
| SrvCount | 0.42 |
| DstHostCount | 0.37 |

*Table D.7: Feature selection for Abalone using Pearson's r and Kendall's tau*

| Sample size | Selection criteria (Number of selected features) | Selected features | | | | |
|---|---|---|---|---|---|---|
| | | Feature | Mean $Corr_{CF}$ | StDev | 95% CI of mean | |
| | | | | | Low | High |
| 500 and 1000 | Pearson's r: t-test (5) probes do not eliminate any features | Diameter | 0.41 | 0.02 | 0.40 | 0.42 |
| | | ShellWeight | 0.4 | 0.02 | 0.39 | 0.41 |
| | | WholeWeight | 0.38 | 0.02 | 0.37 | 0.39 |
| | | VisceraWeight | 0.38 | 0.02 | 0.37 | 0.39 |
| | | ShuckledWeight | 0.34 | 0.02 | 0.33 | 0.35 |
| 500 | Kendall's tau: t-test (6) probes do not eliminate any features | Height | 0.52 | 0.03 | 0.50 | 0.54 |
| | | ShellWeight | 0.53 | 0.03 | 0.51 | 0.55 |
| | | Diameter | 0.5 | 0.03 | 0.48 | 0.52 |
| | | VisceraWeight | 0.49 | 0.03 | 0.47 | 0.51 |
| | | ShuckledWeight | 0.45 | 0.03 | 0.43 | 0.47 |
| | | WholeWeight | 0.5 | 0.03 | 0.48 | 0.52 |
| 1000 | Kendall's tau: t-test (7) probes do not eliminate any features | ShellWeight | 0.52 | 0.02 | 0.51 | 0.53 |
| | | Height | 0.51 | 0.02 | 0.50 | 0.52 |
| | | Diameter | 0.5 | 0.02 | 0.49 | 0.51 |
| | | WholeWeight | 0.49 | 0.02 | 0.48 | 0.50 |
| | | VisceraWeight | 0.49 | 0.02 | 0.48 | 0.50 |
| | | ShuckledWeight | 0.45 | 0.02 | 0.44 | 0.46 |
| | | Length | 0.17 | 0.01 | 0.16 | 0.18 |
| 1000 | Decision rule (3) | ShellWeight | 0.53 | 0.03 | 0.51 | 0.55 |
| | | Length | 0.17 | 0.01 | 0.16 | 0.18 |
| | | Gender | 0.12 | 0.01 | 0.11 | 0.13 |

*Table D.8: Abalone3C feature-feature correlations*

| Feature1 | Feature2 | $corr_{ff}$ | Feature1 | Feature2 | $corr_{ff}$ |
|---|---|---|---|---|---|
| Length | Diameter | 0.92 | Height | ShellWeight | 0.79 |
| Length | Height | 0.75 | WholeWeight | ShuckledWeight | 0.88 |
| Length | WholeWeight | 0.88 | WholeWeight | VisceraWeight | 0.87 |
| Length | ShuckledWeight | 0.84 | WholeWeight | ShellWeight | 0.86 |
| Length | VisceraWeight | 0.83 | ShuckledWeight | VisceraWeight | 0.80 |
| Length | ShellWeight | 0.83 | ShuckledWeight | ShellWeight | 0.76 |
| Diameter | Height | 0.77 | VisceraWeight | ShellWeight | 0.80 |
| Diameter | WholeWeight | 0.88 | Length | Gender | 0.11 |
| Diameter | ShuckledWeight | 0.83 | Diameter | Gender | 0.46 |
| Diameter | VisceraWeight | 0.83 | Height | Gender | 0.47 |
| Diameter | ShellWeight | 0.85 | WholeWeight | Gender | 0.48 |
| Height | WholeWeight | 0.78 | ShuckledWeight | Gender | 0.46 |
| Height | ShuckledWeight | 0.72 | VisceraWeight | Gender | 0.49 |
| Height | VisceraWeight | 0.76 | ShellWeight | Gender | 0.47 |

*Table D9: Feature selection for mushroom using SU coefficients*

| Sample size for SU measurement | Selection criteria (Number of selected features) | Selected features or top 5 features | | | |
|---|---|---|---|---|---|
| | | Feature | Mean *SU* | StDev | 95% CI of mean |
| 500 | t-test (4) | Ordor | 0.55 | 0.03 | 0.02 |
| | | SporePrintColor | 0.3 | 0.02 | 0.01 |
| | | RingType | 0.23 | 0.01 | 0.01 |
| | | GillColor | 0.2 | 0.02 | 0.01 |
| 500 | Uniform probe (15)<br>Uniform binary probe (14)<br>Gaussian probe (21) | Ordor | 0.55 | 0.03 | 0.02 |
| | | SporePrintColor | 0.3 | 0.02 | 0.01 |
| | | StalkSfAbvRing | 0.28 | 0.03 | 0.02 |
| | | GillSize | 0.24 | 0.03 | 0.02 |
| | | StalkSfBlRing | 0.23 | 0.03 | 0.02 |
| 500 | Decision rule (14) | Ordor | 0.55 | 0.03 | 0.02 |
| | | SporePrintColor | 0.30 | 0.02 | 0.02 |
| | | StalkSfAbvRing | 0.28 | 0.03 | 0.02 |
| | | GillSize | 0.24 | 0.03 | 0.02 |
| | | StalkSfBlRing | 0.23 | 0.03 | 0.02 |
| | | RingType | 0.23 | 0.01 | 0.01 |
| | | GillColor | 0.20 | 0.02 | 0.01 |
| | | StalkClAbvRing | 0.18 | 0.02 | 0.01 |
| | | Bruises | 0.17 | 0.03 | 0.02 |
| | | StalkClBlRing | 0.15 | 0.02 | 0.01 |
| | | Population | 0.14 | 0.02 | 0.01 |
| | | GillSpace | 0.14 | 0.03 | 0.02 |
| | | habitat | 0.11 | 0.01 | 0.01 |
| | | StalkRoot | 0.10 | 0.01 | 0.01 |

# Appendix E

# Algorithm for breadth first generation of a search space

This appendix provides the details of the standard breadth-first search algorithm and the *BreadthFirstGenerate* algorithm which is based on the breadth first algorithm. The *BreadthFirstGenerate* algorithm was used for the generation of all possible tied predictions as discussed in section 6.4. The standard breadth-first search algorithm (Luger & Stubblefield, 1993) is given in figure E.1. The *BreadthFirstGenerate* algorithm is given in figure E.2.

Both algorithms use the lists OPEN, CLOSED and CHILDREN. The OPEN list holds the states that are still to be expanded. The CLOSED list holds all states that have been generated so far. The CHILDREN list is used to temporarily hold all the children (successor states) of the current state while the children are being generated. The major difference between the breadth-first-search algorithm and the BreadthFirstGenerate algorithm is that the breadth-first-search algorithm specifically searches for a goal state while the BreadthFirstGenerate algorithm simply generates all the possible states in the search space.

```
Breadth-first-search
1. OPEN = [start_state]
2. CLOSED = [ ]
3. while OPEN ≠ [ ]
   begin
          3.1  Remove leftmost state from OPEN, and call it X
          3.2  if X is the goal state
                    return X
          else
          3.2  generate children of X and put them on the CHILDREN list
          3.3 eliminate children of X on OPEN (prevent cycles)
          3.4  put X on CLOSED
          3.5 put all states on CHILDREN list on right end of OPEN
  end
```

*Figure E.1: Breadth-first search algorithm*

```
BreadthFirstGenerate( )
1. OPEN = [start_state]
2. CLOSED = [ ]
3. while OPEN ≠ [ ]
   begin
        3.1  Remove leftmost state from OPEN and  call it X
        3.2  generate children of X and put them on the CHILDREN list
        3.3  put X on CLOSED
        3.4 put all states on CHILDREN list on right end of OPEN
  end
```

*Figure E.2: BreadthFirstGenerate algorithm*

For the generation of all possible tied predictions, the predictions are assigned numbers 1,2,..,$k$ corresponding to the $k$ classes for the prediction task. The start state contains the first number (1). Each state {1,.., $j$} has the children $j$+1, $j$+2,..,,$k$. When the *BreadthFirstGenerate* algorithm has finished executing, all the possible states (tied predictions) are available on the CLOSED list.

Given a search space represented by a search tree with a constant branching factor $B$, the number of states (paths) of length $L$ generated by a search algorithm is given by (Luger & Stubblefield, 1993: pg 146)

$$States = B + B^2 + B^3 + \ldots + B^L \tag{E.1}$$

which reduces to:

$$States = B(B^L - 1)/(B-1) \tag{E.2}$$

For the *BreadthFirstGenerate* algorithm, the branching factor for level 1 of the tree is $k$ -1 and reduces by 1 for successive levels. The maximum path length is $k$ so that

$$States = (k-1) + (k-2)^2 + \ldots + (k-(k-1))^k \tag{E.3}$$

which reduces to:

$$States = \sum_{j=1}^{k} (k-j)^j \tag{E.4}$$

# Appendix F

# Predictive performance of single OVA and pVn models

The detailed results for predictive accuracy and TPRATE values for the single *k*-class, OVA aggregate and pVn aggregate models using the 5NN and See5 algorithms are provided in this appendix. Each table shows the accuracy and class TPRATE values for 10 test samples, as well as the mean, 95% confidence interval of the mean, standard deviation and variance. The mean values for performance were discussed in chapters 7 and 8. The variance values were used for the F-tests discussed in chapter 8.

## F.1 5NN single 7-class and aggregate models for forest cover type

Tables F.1 to F.4 give the details of predictive accuracy and TRATE values for the 5NN single 7-class, OVA and pVn aggregate models forest cover type.

*Table F.1: Predictive performance of the 5NN single 7- class model for forest cover type*

| Test set | Accuracy on all classes | 5NN single model (equal class distribution) TPRATE% for class: | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 1 | 75.4 | 68 | 48 | 58 | 98 | 88 | 72 | 96 |
| 2 | 71.4 | 60 | 46 | 50 | 90 | 92 | 70 | 92 |
| 3 | 75.1 | 60 | 48 | 64 | 96 | 88 | 76 | 94 |
| 4 | 73.7 | 66 | 50 | 48 | 90 | 92 | 74 | 96 |
| 5 | 72.6 | 54 | 42 | 56 | 92 | 94 | 76 | 94 |
| 6 | 76.9 | 72 | 50 | 48 | 94 | 94 | 82 | 98 |
| 7 | 74.6 | 60 | 50 | 58 | 90 | 90 | 76 | 98 |
| 8 | 76 | 60 | 58 | 68 | 90 | 86 | 72 | 98 |
| 9 | 75.4 | 60 | 52 | 58 | 94 | 92 | 74 | 98 |
| 10 | 76 | 68 | 44 | 60 | 90 | 96 | 78 | 96 |
| **Mean** | **74.7** | **62.8** | **48.8** | **56.8** | **92.4** | **91.2** | **75.0** | **96.0** |
| **StDev** | **1.7** | **5.4** | **4.4** | **6.6** | **3.0** | **3.2** | **3.4** | **2.1** |
| **Variance** | **2.9** | **29.5** | **19.7** | **43.7** | **8.7** | **10.0** | **11.8** | **4.4** |
| **Mean & CI** | **74.7±1.0** | **62.8±3.4** | **48.8±2.8** | **56.8±4.1** | **92.4±1.8** | **91.2±2.0** | **75.0±2.1** | **96.0±1.3** |

*Table F.2: Predictive performance of the 5NN un-boosted OVA aggregate model for forest cover type*

| Test set | Accuracy on all classes | 5NN un-boosted OVA aggregate model. TPRATE% for class: | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 1 | 78.3 | 74 | 58 | 72 | 96 | 86 | 64 | 98 |
| 2 | 80.3 | 68 | 64 | 68 | 92 | 94 | 78 | 98 |
| 3 | 82.9 | 78 | 58 | 76 | 92 | 96 | 84 | 96 |
| 4 | 80.6 | 84 | 58 | 70 | 86 | 88 | 82 | 96 |
| 5 | 80.9 | 70 | 58 | 68 | 88 | 100 | 86 | 96 |
| 6 | 79.1 | 62 | 60 | 70 | 88 | 100 | 78 | 96 |
| 7 | 79.1 | 62 | 52 | 70 | 92 | 98 | 82 | 98 |
| 8 | 82.0 | 66 | 66 | 76 | 88 | 100 | 82 | 96 |
| 9 | 82.0 | 68 | 58 | 74 | 88 | 98 | 92 | 96 |
| 10 | 79.4 | 68 | 52 | 74 | 88 | 98 | 80 | 96 |
| **Mean** | **80.5** | **70.0** | **58.4** | **71.8** | **89.8** | **95.8** | **80.8** | **96.6** |
| **StDev** | **1.5** | **6.9** | **4.4** | **3.0** | **3.0** | **5.0** | **7.2** | **1.0** |
| **Variance** | **2.3** | **48.0** | **19.4** | **9.3** | **9.3** | **25.3** | **51.7** | **0.9** |
| **Mean&CI** | **80.5±0.9** | **70±4.3** | **58.4±2.7** | **71.8±1.9** | **89.8±1.9** | **95.8±3.1** | **80.8±4.5** | **96.6±0.6** |

*TableF.3: Predictive performance of the 5NN boosted OVA aggregate model for forest cover type*

| Test set | Accuracy on all classes | 5NN boosted OVA aggregate model. TPRATE% for class: | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 1 | 82.9 | 74 | 62 | 74 | 100 | 98 | 74 | 98 |
| 2 | 82.3 | 68 | 70 | 70 | 100 | 98 | 72 | 98 |
| 3 | 82.6 | 78 | 58 | 72 | 100 | 94 | 80 | 96 |
| 4 | 83.7 | 84 | 62 | 68 | 100 | 98 | 78 | 96 |
| 5 | 81.4 | 70 | 60 | 68 | 100 | 96 | 80 | 96 |
| 6 | 81.4 | 62 | 60 | 72 | 100 | 98 | 82 | 96 |
| 7 | 80.9 | 62 | 58 | 74 | 100 | 96 | 78 | 98 |
| 8 | 82.3 | 66 | 72 | 72 | 100 | 96 | 74 | 96 |
| 9 | 82.3 | 68 | 64 | 70 | 100 | 98 | 80 | 96 |
| 10 | 80.6 | 68 | 54 | 70 | 100 | 98 | 78 | 96 |
| **Mean** | **82.0** | **70.0** | **62.0** | **71.0** | **100.0** | **97.0** | **77.6** | **96.6** |
| **StDev** | **1.0** | **6.9** | **5.5** | **2.2** | **0.0** | **1.4** | **3.2** | **1.0** |
| **Variance** | **0.9** | **48.0** | **30.2** | **4.7** | **0.0** | **2.0** | **10.5** | **0.9** |
| **Mean &CI** | **82.0±0.6** | **70.0±4.3** | **62.0±3.4** | **71.0±1.3** | **100.0±0.0** | **97.0±0.9** | **77.6±2.0** | **96.6±0.6** |

*Table F.4: Predictive performance of the 5NN pVn aggregate model for forest cover type*

| Test set | Accuracy on all classes | 5NN pVn aggregate model. TPRATE% for class: | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 1 | 78.3 | 68 | 52 | 70 | 98 | 90 | 70 | 100 |
| 2 | 75.1 | 60 | 60 | 66 | 94 | 90 | 68 | 88 |
| 3 | 81.4 | 82 | 58 | 68 | 100 | 94 | 74 | 94 |
| 4 | 79.7 | 80 | 56 | 64 | 96 | 94 | 76 | 92 |
| 5 | 79.1 | 70 | 60 | 62 | 98 | 98 | 78 | 88 |
| 6 | 80.0 | 70 | 58 | 60 | 98 | 98 | 82 | 94 |
| 7 | 76.0 | 66 | 52 | 64 | 94 | 94 | 72 | 90 |
| 8 | 77.7 | 62 | 60 | 66 | 98 | 90 | 74 | 94 |
| 9 | 80.3 | 64 | 62 | 70 | 98 | 96 | 74 | 98 |
| 10 | 78.0 | 56 | 60 | 60 | 96 | 98 | 82 | 94 |
| **Mean** | **78.6** | **67.8** | **57.8** | **65.0** | **97.0** | **94.2** | **75.0** | **93.2** |
| **StDev** | **2.0** | **8.2** | **3.5** | **3.7** | **1.9** | **3.3** | **4.6** | **3.9** |
| **Variance** | **3.8** | **68.0** | **12.0** | **13.6** | **3.8** | **11.1** | **21.6** | **15.3** |
| **Mean&CI** | **78.6±1.2** | **67.8±5.1** | **57.8±2.1** | **65.0±2.3** | **97.0±1.2** | **94.2±2.1** | **75.0±2.9** | **93.2±2.4** |

## F.2 See5 single 7-class and aggregate models for forest cover type

Tables F.5 to F.8 give the details of predictive accuracy and TPRATE values for the See5 single 7-class, OVA and pVn aggregate models for the forest cover type dataset.

*Table F.5: Predictive performance of the See5 single 7-class model for forest cover type*

| **Test set** | Accuracy on **all classes** | See5 single model (equal class distribution). TPRATE% for class: | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** |
| 1 | 77.1 | 56 | 60 | 68 | 100 | 92 | 70 | 94 |
| 2 | 76 | 68 | 58 | 60 | 96 | 86 | 70 | 94 |
| 3 | 78 | 52 | 66 | 68 | 98 | 86 | 80 | 96 |
| 4 | 76 | 52 | 62 | 64 | 96 | 86 | 80 | 92 |
| 5 | 77.1 | 66 | 62 | 54 | 94 | 92 | 80 | 92 |
| 6 | 78.9 | 58 | 74 | 58 | 98 | 90 | 78 | 96 |
| 7 | 73.7 | 54 | 58 | 54 | 96 | 82 | 74 | 98 |
| 8 | 76 | 56 | 66 | 56 | 96 | 82 | 78 | 98 |
| 9 | 78.9 | 58 | 66 | 64 | 98 | 82 | 88 | 96 |
| 10 | 77.4 | 54 | 66 | 62 | 96 | 84 | 80 | 100 |
| **Mean** | **76.91** | **57.40** | **63.80** | **60.80** | **96.80** | **86.20** | **77.80** | **95.60** |
| **StDev** | **1.57** | **5.50** | **4.85** | **5.27** | **1.69** | **3.94** | **5.37** | **2.63** |
| **Variance** | **2.47** | **30.27** | **23.51** | **27.73** | **2.84** | **15.51** | **28.84** | **6.93** |
| **Mean & CI** | **76.9±1.0** | **57.4±3.4** | **63.8±3.0** | **60.8±3.3** | **96.8±1.0** | **86.2±2.4** | **77.8±3.3** | **95.6±1.6** |

*Table F.6: Predictive performance of See5 un-boosted OVA aggregate model for forest cover type*

| Test sample | Accuracy on all classes | See5 un-boosted OVA aggregate model. TPRATE% for class: | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 1 | 74.9 | 64 | 44 | 68 | 84 | 96 | 80 | 88 |
| 2 | 75.7 | 62 | 52 | 66 | 88 | 94 | 78 | 90 |
| 3 | 75.1 | 60 | 50 | 60 | 92 | 90 | 78 | 96 |
| 4 | 73.7 | 60 | 40 | 62 | 88 | 96 | 80 | 90 |
| 5 | 74.3 | 60 | 44 | 64 | 86 | 98 | 78 | 90 |
| 6 | 77.1 | 68 | 58 | 60 | 86 | 98 | 80 | 90 |
| 7 | 74.6 | 58 | 50 | 66 | 88 | 94 | 72 | 94 |
| 8 | 75.1 | 54 | 52 | 66 | 82 | 96 | 80 | 100 |
| 9 | 76.9 | 64 | 50 | 66 | 86 | 92 | 82 | 98 |
| 10 | 75.4 | 56 | 58 | 62 | 86 | 90 | 84 | 92 |
| **Mean** | **75.3** | **60.6** | **49.8** | **64.0** | **86.6** | **94.4** | **79.2** | **92.8** |
| **StDev** | **1.1** | **4.1** | **5.8** | **2.8** | **2.7** | **3.0** | **3.2** | **4.0** |
| **Variance** | **1.1** | **16.9** | **34.2** | **8.0** | **7.2** | **8.7** | **10.0** | **16.2** |
| **Mean&CI** | **75.3±0.7** | **60.6±2.6** | **49.8±3.6** | **64.0±1.8** | **86.6±1.7** | **94.4±1.8** | **79.2±2.0** | **92.8±2.5** |

*Table F.7: Predictive performance of See5 boosted OVA aggregate model for forest cover type*

| **Test set** | Accuracy on all classes | See5 boosted OVA aggregate model. TPRATE% for class: | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** |
| 1 | 79.4 | 70 | 70 | 72 | 96 | 82 | 70 | 96 |
| 2 | 80.3 | 68 | 66 | 70 | 94 | 92 | 74 | 98 |
| 3 | 80 | 60 | 66 | 66 | 100 | 90 | 78 | 100 |
| 4 | 77.7 | 62 | 66 | 62 | 94 | 86 | 78 | 96 |
| 5 | 78.9 | 60 | 70 | 60 | 96 | 92 | 78 | 96 |
| 6 | 80.3 | 70 | 76 | 54 | 96 | 90 | 78 | 98 |
| 7 | 78.9 | 62 | 74 | 60 | 96 | 90 | 72 | 98 |
| 8 | 78.6 | 66 | 70 | 60 | 92 | 90 | 76 | 96 |
| 9 | 80.6 | 72 | 66 | 62 | 94 | 90 | 80 | 100 |
| 10 | 79.1 | 60 | 74 | 66 | 96 | 82 | 76 | 100 |
| **Mean** | **79.38** | **65.00** | **69.80** | **63.20** | **95.40** | **88.40** | **76.00** | **97.80** |
| **StDev** | **0.92** | **4.74** | **3.82** | **5.35** | **2.12** | **3.75** | **3.13** | **1.75** |
| **Variance** | **0.84** | **22.44** | **14.62** | **28.62** | **4.49** | **14.04** | **9.78** | **3.07** |
| **Mean & CI** | **79.4±0.6** | **65.0±2.9** | **69.8±2.4** | **63.2±3.3** | **95.4±1.3** | **88.4±2.3** | **76.0±1.9** | **97.8±1.1** |

Table F.8: Predictive performance of the See5 pVn aggregate model for forest cover type

| Test set | Accuracy on all classes | See5 pVn aggregate model. TPRATE% for class: | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** |
| 1 | 78 | 72 | 56 | 72 | 94 | 84 | 78 | 90 |
| 2 | 79.1 | 70 | 58 | 74 | 92 | 92 | 82 | 86 |
| 3 | 80.6 | 64 | 62 | 76 | 100 | 88 | 78 | 96 |
| 4 | 79.4 | 62 | 68 | 76 | 94 | 88 | 82 | 86 |
| 5 | 80 | 62 | 66 | 74 | 96 | 88 | 86 | 88 |
| 6 | 79.7 | 64 | 74 | 58 | 92 | 92 | 88 | 90 |
| 7 | 78.6 | 66 | 58 | 70 | 98 | 86 | 76 | 96 |
| 8 | 80.3 | 62 | 72 | 70 | 94 | 90 | 80 | 94 |
| 9 | 83.7 | 68 | 74 | 76 | 92 | 92 | 88 | 96 |
| 10 | 79.1 | 56 | 64 | 72 | 94 | 86 | 84 | 98 |
| **Mean** | **79.85** | **64.60** | **65.20** | **71.80** | **94.60** | **88.60** | **82.20** | **92.00** |
| **StDev** | **1.56** | **4.62** | **6.75** | **5.37** | **2.67** | **2.84** | **4.26** | **4.52** |
| **Variance** | **2.44** | **21.38** | **45.51** | **28.84** | **7.16** | **8.04** | **18.18** | **20.44** |
| **Mean& CI** | **79.9±1.0** | **64.6±2.9** | **65.2±4.2** | **71.8±3.3** | **94.6±1.7** | **88.6±1.8** | **82.2±2.6** | **92.0±2.8** |

## F.3 5NN single 5-class and aggregate models for KDD Cup 1999

Tables F.9 to F.12 give the details of predictive accuracy and TPRATE values for the 5NN single 5-class, OVA and pVn aggregate models KDD Cup 1999.

Table F.9: Predictive performance of the 5NN single 5-class model for KDD Cup 1999

| Test set | Accuracy on all classes | 5NN single model (equal class distribution for NORMAL, DOS, PROBE, R2L). TPRATE% for class: | | | | |
|---|---|---|---|---|---|---|
| | | **NORMAL** | **DOS** | **PROBE** | **R2L** | **U2R** |
| 1 | 69.7 | 81.4 | 80 | 95.7 | 60 | 31.4 |
| 2 | 72 | 87.1 | 72.9 | 97.1 | 71.4 | 31.4 |
| 3 | 65.7 | 87.1 | 51.4 | 98.6 | 60 | 31.4 |
| 4 | 71.1 | 94.3 | 61.4 | 94.3 | 72.9 | 32.9 |
| 5 | 68.3 | 81.4 | 62.9 | 92.9 | 72.9 | 31.4 |
| 6 | 66.3 | 85.7 | 60 | 94.3 | 60 | 31.4 |
| 7 | 69.7 | 87.1 | 71.4 | 94.3 | 64.3 | 31.4 |
| 8 | 66.3 | 81.4 | 67.1 | 94.3 | 57.1 | 31.4 |
| 9 | 69.7 | 82.8 | 71.4 | 98.6 | 64.3 | 31.4 |
| 10 | 66.6 | 75.7 | 64.3 | 97.1 | 64.3 | 31.4 |
| **Mean** | **68.54** | **84.40** | **66.28** | **95.72** | **64.72** | **31.55** |
| **StDev** | **2.22** | **5.02** | **8.06** | **2.01** | **5.81** | **0.47** |
| **Variance** | **4.94** | **25.20** | **65.02** | **4.05** | **33.76** | **0.22** |
| **Mean & CI** | **68.5 ± 1.4** | **84.4 ± 3.1** | **66.3 ± 5.0** | **95.7 ± 1.2** | **64.7 ± 3.6** | **31.6 ± 0.3** |

*Table F.10: Predictive performance of the 5NN OVA un-boosted aggregate model for KDD Cup 1999*

| Test set | Accuracy on all classes | 5NN un-boosted OVA aggregate model. TPRATE % for class: | | | | |
|---|---|---|---|---|---|---|
| | | NORMAL | DOS | PROBE | R2L | U2R |
| 1 | 73.7 | 90 | 81.4 | 94.3 | 61.4 | 41.4 |
| 2 | 73.4 | 92.9 | 68.6 | 95.7 | 67.1 | 42.9 |
| 3 | 72.3 | 98.6 | 58.6 | 98.6 | 62.9 | 42.9 |
| 4 | 73.1 | 97.1 | 61.4 | 94.3 | 71.4 | 41.4 |
| 5 | 71.7 | 85.7 | 64.3 | 92.9 | 72.9 | 42.9 |
| 6 | 69.4 | 91.4 | 57.1 | 94.3 | 61.4 | 42.9 |
| 7 | 73.7 | 94.3 | 68.6 | 95.7 | 67.1 | 42.9 |
| 8 | 69.1 | 87.1 | 65.7 | 94.3 | 55.7 | 42.9 |
| 9 | 74.3 | 98.6 | 71.4 | 97.1 | 61.4 | 42.9 |
| 10 | 72.9 | 91.4 | 62.9 | 94.3 | 72.9 | 42.9 |
| **Mean** | **72.4** | **92.7** | **66.0** | **95.2** | **65.4** | **42.6** |
| **StDev** | **1.8** | **4.5** | **7.1** | **1.7** | **5.8** | **0.6** |
| **Variance** | **3.2** | **20.3** | **49.7** | **2.8** | **33.6** | **0.4** |
| **CI of mean** | **1.1** | **2.8** | **4.4** | **1.0** | **3.6** | **0.4** |
| **Mean&CI** | **72.4±1.1** | **92.7±2.8** | **66.0±4.4** | **95.2±1.0** | **65.4±3.6** | **42.6±0.4** |

*Table F.11: Predictive performance of the 5NN OVA boosted aggregate model for KDD Cup 1999*

| Test set | Accuracy on all classes | 5NN boosted OVA aggregate model. TPRATE% for class: | | | | |
|---|---|---|---|---|---|---|
| | | NORMAL | DOS | PROBE | R2L | U2R |
| 1 | 73.7 | 90 | 82.9 | 94.3 | 58.6 | 42.9 |
| 2 | 73.4 | 94.3 | 68.6 | 95.7 | 65.7 | 42.9 |
| 3 | 70.0 | 98.6 | 52.9 | 98.6 | 57.1 | 42.9 |
| 4 | 72.3 | 97.1 | 61.4 | 94.3 | 65.7 | 42.9 |
| 5 | 70.9 | 85.7 | 64.3 | 92.9 | 74.3 | 37.1 |
| 6 | 68.0 | 90 | 58.6 | 94.3 | 57.1 | 40 |
| 7 | 71.4 | 94.3 | 70 | 95.7 | 58.6 | 38.6 |
| 8 | 68.3 | 85.7 | 67.1 | 94.3 | 55.7 | 38.6 |
| 9 | 72.3 | 98.6 | 71.4 | 98.6 | 54.3 | 38.6 |
| 10 | 70.0 | 90 | 62.9 | 95.7 | 61.4 | 40 |
| **Mean** | **71.0** | **92.4** | **66.0** | **95.4** | **60.9** | **40.5** |
| **StDev** | **2.0** | **4.9** | **8.2** | **1.9** | **6.1** | **2.3** |
| **Variance** | **3.9** | **23.7** | **66.5** | **3.5** | **37.3** | **5.1** |
| **CI of mean** | **1.2** | **3.0** | **5.1** | **1.2** | **3.8** | **1.4** |
| **Mean&CI** | **71.0±1.2** | **92.4±3.0** | **66.0±5.1** | **95.4±1.2** | **60.9±3.8** | **40.5±1.4** |

Table F.12: Predictive performance of the 5NN pVn aggregate model for KDD Cup 1999

| Test sample | Accuracy on all classes | 5NN pVn aggregate model. TPRATE% for class: | | | | |
|---|---|---|---|---|---|---|
| | | NORMAL | DOS | PROBE | R2L | U2R |
| 1 | 79.4 | 97.1 | 100 | 98.6 | 72.9 | 28.6 |
| 2 | 82.0 | 98.6 | 98.6 | 98.6 | 88.6 | 27.1 |
| 3 | 80.6 | 100 | 95.7 | 100 | 81.4 | 25.7 |
| 4 | 82.0 | 100 | 98.6 | 98.6 | 85.7 | 25.7 |
| 5 | 81.0 | 100 | 98.6 | 97.1 | 85.7 | 25.7 |
| 6 | 78.0 | 95.7 | 94.3 | 100 | 77.1 | 21.4 |
| 7 | 83.0 | 100 | 98.6 | 98.6 | 87.1 | 31.4 |
| 8 | 80.0 | 98.6 | 100 | 97.1 | 74.3 | 28.6 |
| 9 | 77.1 | 98.6 | 91.4 | 100 | 72.9 | 22.9 |
| 10 | 80.0 | 98.6 | 97.1 | 95.7 | 88.6 | 20 |
| **Mean** | **80.3** | **98.7** | **97.3** | **98.4** | **81.4** | **25.7** |
| **StDev** | **1.8** | **1.4** | **2.7** | **1.4** | **6.6** | **3.5** |
| **Variance** | **3.4** | **2.0** | **7.5** | **2.1** | **42.9** | **12.2** |
| **Mean&CI** | **80.3±1.1** | **98.7±0.9** | **97.3±1.7** | **98.4±0.9** | **81.4±4.1** | **25.7±2.2** |

## F.4 See5 single 5-class and aggregate models for KDD Cup 1999

Tables F.13 to F.16 give the details of predictive accuracy and TPRATE values for the See5 single 5-class, OVA and pVn aggregate models KDD Cup 1999.

Table F.13: Predictive performance of the See5 single model for KDD Cup 1999

| **Test set** | Accuracy on all classes | See5 single model (equal class distribution for NORMAL, DOS, PROBE, R2L). TPRATE% for class: | | | | |
|---|---|---|---|---|---|---|
| | | **NORMAL** | **DOS** | **PROBE** | **R2L** | **U2R** |
| 1 | 65.1 | 84.3 | 84.3 | 44.3 | 35.7 | 77.1 |
| 2 | 66.0 | 91.4 | 75.7 | 38.6 | 47.1 | 77.1 |
| 3 | 63.1 | 91.4 | 77.1 | 34.3 | 35.7 | 77.1 |
| 4 | 63.7 | 88.6 | 85.7 | 35.7 | 31.4 | 77.1 |
| 5 | 67.1 | 82.9 | 95.7 | 34.3 | 45.7 | 77.1 |
| 6 | 63.4 | 90.0 | 85.7 | 31.4 | 32.9 | 77.1 |
| 7 | 65.4 | 90.0 | 81.4 | 38.6 | 40.0 | 77.1 |
| 8 | 60.0 | 80.0 | 78.6 | 31.4 | 32.9 | 77.1 |
| 9 | 63.4 | 84.3 | 77.1 | 38.6 | 40.0 | 77.1 |
| 10 | 61.1 | 77.1 | 78.6 | 37.1 | 35.7 | 77.1 |
| **Mean** | **63.83** | **86.00** | **81.99** | **36.43** | **37.71** | **77.10** |
| **StDev** | **2.17** | **5.03** | **6.07** | **3.90** | **5.38** | **0.00** |
| **Variance** | **4.72** | **25.30** | **36.84** | **15.19** | **28.97** | **0.00** |
| **Mean & CI** | **63.8±1.3** | **86.0±3.1** | **82.0±3.8** | **36.4±2.4** | **37.7±3.3** | **77.1±0.0** |

*Table F.14: Predictive performance of the See5 un-boosted OVA aggregate model for KDD Cup1999*

| Test set | Accuracy on all classes | See5 Class TPRATE% - boosted AGGREGATE MODEL | | | | |
|---|---|---|---|---|---|---|
| | | **NORMAL** | **DOS** | **PROBE** | **R2L** | **U2R** |
| 1 | 62.3 | 97.1 | 45.7 | 88.6 | 34.3 | 45.7 |
| 2 | 65.7 | 100 | 54.3 | 87.1 | 41.4 | 45.7 |
| 3 | 60.9 | 98.6 | 42.9 | 85.7 | 31.4 | 45.7 |
| 4 | 66.6 | 98.6 | 61.4 | 88.6 | 38.6 | 45.7 |
| 5 | 64.9 | 98.6 | 54.3 | 84.3 | 41.1 | 45.7 |
| 6 | 61.1 | 97.1 | 37.1 | 91.4 | 34.3 | 45.7 |
| 7 | 64.3 | 98.6 | 55.7 | 87.1 | 34.3 | 45.7 |
| 8 | 62.3 | 97.1 | 51.4 | 90 | 27.1 | 45.7 |
| 9 | 62.6 | 100 | 52.9 | 88.6 | 25.7 | 45.7 |
| 10 | 62.3 | 97.1 | 45.7 | 88.6 | 34.3 | 45.7 |
| **Mean** | **63.3** | **98.3** | **50.1** | **88.0** | **34.3** | **45.7** |
| **StDev** | **2.0** | **1.1** | **7.2** | **2.0** | **5.3** | **0.0** |
| **Variance** | **3.8** | **1.3** | **51.5** | **4.2** | **27.7** | **0.0** |
| **Mean & CI** | **63.3±1.2** | **98.3±0.7** | **50.1±4.4** | **88.0±1.3** | **34.3±3.3** | **45.7±0.0** |

*Table F.15: Predictive performance of the See5 boosted OVA aggregate model for KDD Cup1999*

| Test set | Accuracy on all classes | See5 boosted OVA aggregate model. TPRATE% for class: | | | | |
|---|---|---|---|---|---|---|
| | | **NORMAL** | **DOS** | **PROBE** | **R2L** | **U2R** |
| 1 | 63.1 | 97.1 | 65.7 | 88.6 | 24.3 | 40.0 |
| 2 | 63.7 | 100.0 | 61.4 | 90.0 | 27.1 | 40.0 |
| 3 | 60.9 | 100.0 | 50.0 | 88.6 | 25.7 | 40.0 |
| 4 | 61.7 | 100.0 | 61.4 | 90.0 | 17.1 | 40.0 |
| 5 | 61.4 | 98.6 | 54.3 | 84.3 | 30.0 | 40.0 |
| 6 | 59.1 | 98.6 | 42.9 | 92.9 | 21.4 | 40.0 |
| 7 | 62.9 | 100.0 | 61.4 | 88.6 | 24.3 | 40.0 |
| 8 | 60.3 | 98.6 | 52.9 | 90.0 | 20.0 | 40.0 |
| 9 | 61.1 | 100.0 | 60.0 | 91.4 | 14.3 | 40.0 |
| 10 | 62.3 | 98.6 | 52.9 | 88.6 | 31.4 | 40.0 |
| **Mean** | **61.65** | **99.15** | **56.29** | **89.30** | **23.56** | **40.00** |
| **StDev** | **1.40** | **1.00** | **6.88** | **2.26** | **5.44** | **0.00** |
| **Variance** | **1.95** | **1.00** | **47.38** | **5.09** | **29.55** | **0.00** |
| **Mean & CI** | **61.7±0.9** | **99.2±0.6** | **56.3±4.3** | **89.3±1.4** | **23.6±3.4** | **40.0±0.0** |

*Table F.16: Predictive performance of the See5 pVn aggregate model for KDD Cup 1999*

| Test sample ID | Accuracy on all classes | See5 pVn aggregate model. TPRATE% for class: | | | | |
|---|---|---|---|---|---|---|
| | | NORMAL | DOS | PROBE | R2L | U2R |
| 1 | 74 | 97.1 | 67.1 | 98.6 | 30 | 77.1 |
| 2 | 79.1 | 98.6 | 57.1 | 97.1 | 65.7 | 77.1 |
| 3 | 78 | 98.6 | 60 | 97.1 | 57.1 | 77.1 |
| 4 | 83.4 | 98.6 | 87.1 | 95.7 | 58.6 | 77.1 |
| 5 | 85.1 | 100 | 84.3 | 97.1 | 67.1 | 77.1 |
| 6 | 78 | 97.1 | 64.3 | 100 | 51.4 | 77.1 |
| 7 | 81.1 | 98.6 | 71.4 | 95.7 | 62.9 | 77.1 |
| 8 | 77.7 | 97.1 | 70 | 97.1 | 47.1 | 77.1 |
| 9 | 74.9 | 98.6 | 55.7 | 97.1 | 45.7 | 77.1 |
| 10 | 78.3 | 97.1 | 67.1 | 94.3 | 55.7 | 77.1 |
| **Mean** | **78.96** | **98.14** | **68.41** | **96.98** | **54.13** | **77.10** |
| **StDev** | **3.45** | **0.99** | **10.51** | **1.57** | **11.16** | **0.00** |
| **Variance** | **11.88** | **0.98** | **110.42** | **2.48** | **124.50** | **0.00** |
| **Mean & CI** | **79.0 ± 2.1** | **98.1 ± 0.6** | **68.4 ± 6.5** | **97.0 ± 1.0** | **54.1 ± 6.9** | **77.1 ± 0.0** |

## F.5 Single and aggregate models for wine quality (white)

Tables F.17 through F.24 give the details of predictive accuracy and TPRATE values for the 5NN single and aggregate models for the wine quality (white) dataset. Tables F.25 and F.26 provide the statistical test results for the comparison of the single and aggregate models.

*Table F.17: Predictive performance of the 5NN single model for Wine quality*

| Test set | Accuracy on all classes | 5NN single model TPRATE% for class: | | | | |
|---|---|---|---|---|---|---|
| | | 4 | 5 | 6 | 7 | 8 |
| 1 | 31.2 | 8 | 56 | 22 | 54 | 8 |
| 2 | 30 | 14 | 58 | 30 | 44 | 4 |
| 3 | 29.2 | 10 | 56 | 24 | 44 | 12 |
| 4 | 28.8 | 6 | 54 | 30 | 46 | 8 |
| 5 | 33.2 | 14 | 54 | 34 | 54 | 10 |
| 6 | 32.4 | 12 | 54 | 34 | 54 | 8 |
| 7 | 30.8 | 14 | 46 | 36 | 44 | 14 |
| 8 | 34 | 18 | 50 | 36 | 54 | 12 |
| 9 | 35.2 | 10 | 64 | 38 | 50 | 14 |
| 10 | 31.6 | 10 | 56 | 30 | 50 | 12 |
| **Mean** | **31.6** | **11.6** | **54.8** | **31.4** | **49.4** | **10.2** |
| **StDev** | **2.1** | **3.5** | **4.7** | **5.3** | **4.5** | **3.2** |
| **Variance** | **4.3** | **12.3** | **22.4** | **27.6** | **20.5** | **10.2** |
| **Mean & CI** | **31.6±1.3** | **11.6±2.2** | **54.8±2.9** | **31.4±3.3** | **49.4±2.8** | **10.2±2.0** |

*Table F.18: Predictive performance of the 5NN un-boosted OVA model for Wine quality*

| Test set | Accuracy on all classes | 5NN OVA un-boosted model TPRATE% for class: | | | | |
|---|---|---|---|---|---|---|
| | | 4 | 5 | 6 | 7 | 8 |
| 1 | 30.4 | 16 | 54 | 24 | 50 | 8 |
| 2 | 32.8 | 14 | 60 | 28 | 56 | 6 |
| 3 | 35.2 | 10 | 64 | 34 | 54 | 14 |
| 4 | 28.8 | 6 | 58 | 32 | 40 | 8 |
| 5 | 33.6 | 14 | 60 | 34 | 52 | 8 |
| 6 | 30.8 | 14 | 54 | 32 | 48 | 6 |
| 7 | 30.4 | 12 | 58 | 26 | 44 | 12 |
| 8 | 34 | 18 | 58 | 30 | 52 | 12 |
| 9 | 32.8 | 10 | 56 | 30 | 54 | 14 |
| 10 | 32.8 | 12 | 68 | 24 | 48 | 12 |
| **Mean** | **32.2** | **12.6** | **59.0** | **29.4** | **49.8** | **10.0** |
| **StDev** | **1.9** | **3.4** | **4.3** | **3.8** | **4.9** | **3.1** |
| **Variance** | **3.8** | **11.6** | **18.9** | **14.3** | **24.4** | **9.8** |
| **Mean & CI** | **32.2±1.2** | **12.6±2.1** | **59.0±2.7** | **29.9±2.3** | **49.8±3.1** | **10.0±1.9** |

*Table F.19: Predictive performance of the 5NN boosted OVA model for Wine quality*

| Test set | Accuracy on all classes | 5NN OVA boosted model TPRATE% for class: | | | | |
|---|---|---|---|---|---|---|
| | | 4 | 5 | 6 | 7 | 8 |
| 1 | 33.2 | 16 | 64 | 24 | 52 | 10 |
| 2 | 33.2 | 16 | 68 | 16 | 58 | 8 |
| 3 | 35.2 | 12 | 68 | 26 | 54 | 16 |
| 4 | 29.2 | 6 | 66 | 22 | 44 | 8 |
| 5 | 35.2 | 16 | 64 | 34 | 52 | 10 |
| 6 | 29.6 | 14 | 62 | 16 | 50 | 6 |
| 7 | 35.2 | 14 | 68 | 34 | 44 | 16 |
| 8 | 35.6 | 18 | 62 | 28 | 56 | 14 |
| 9 | 34.4 | 12 | 64 | 22 | 60 | 14 |
| 10 | 34.8 | 12 | 70 | 28 | 52 | 12 |
| **Mean** | **33.6** | **13.6** | **65.6** | **25.0** | **52.2** | **11.4** |
| **StDev** | **2.3** | **3.4** | **2.8** | **6.3** | **5.3** | **3.5** |
| **Variance** | **5.5** | **11.4** | **7.8** | **40.2** | **28.0** | **12.5** |
| **Mean & CI** | **33.6±1.5** | **13.6±2.1** | **65.6±1.7** | **25.0±3.9** | **52.2±3.3** | **11.4±2.2** |

Table F.20: *Predictive performance of the 5NN pVn model for Wine quality*

| Test set | Accuracy on all classes | 5NN pVn aggregate model TPRATE% for class: | | | | |
|---|---|---|---|---|---|---|
| | | 4 | 5 | 6 | 7 | 8 |
| 1 | 33.2 | 16 | 44 | 52 | 46 | 8 |
| 2 | 34.8 | 12 | 56 | 50 | 50 | 6 |
| 3 | 36 | 12 | 58 | 50 | 46 | 14 |
| 4 | 31.2 | 4 | 54 | 58 | 32 | 8 |
| 5 | 37.6 | 14 | 60 | 60 | 44 | 10 |
| 6 | 32.4 | 12 | 54 | 54 | 34 | 8 |
| 7 | 32.4 | 10 | 56 | 46 | 36 | 14 |
| 8 | 35.6 | 18 | 52 | 42 | 54 | 12 |
| 9 | 34 | 6 | 50 | 50 | 50 | 14 |
| 10 | 38.4 | 10 | 66 | 54 | 50 | 12 |
| **Mean** | **34.6** | **11.4** | **55.0** | **51.6** | **44.2** | **10.6** |
| **StDev** | **2.4** | **4.2** | **5.9** | **5.3** | **7.6** | **3.0** |
| **Variance** | **5.6** | **17.8** | **34.9** | **28.3** | **58.2** | **8.9** |
| **Mean & CI** | **34.6±1.5** | **11.4±2.6** | **55.0±3.7** | **51.6±3.3** | **44.2±4.7** | **10.6±1.9** |

Table F.21: *Predictive performance of the See5 single model for Wine quality*

| Test set | Accuracy on all classes | See5 single model TPRATE% for class: | | | | |
|---|---|---|---|---|---|---|
| | | 4 | 5 | 6 | 7 | 8 |
| 1 | 38.4 | 28 | 70 | 32 | 54 | 8 |
| 2 | 37.6 | 24 | 70 | 34 | 52 | 8 |
| 3 | 38.4 | 28 | 74 | 32 | 50 | 8 |
| 4 | 33.6 | 20 | 64 | 26 | 46 | 12 |
| 5 | 36.4 | 28 | 70 | 32 | 48 | 4 |
| 6 | 37.2 | 30 | 72 | 30 | 46 | 8 |
| 7 | 36.8 | 28 | 70 | 36 | 44 | 6 |
| 8 | 37.2 | 28 | 66 | 36 | 46 | 10 |
| 9 | 38 | 26 | 70 | 34 | 50 | 10 |
| 10 | 34 | 20 | 74 | 30 | 42 | |
| **Mean** | **36.8** | **26.0** | **70.0** | **32.2** | **47.8** | **8.2** |
| **StDev** | **1.7** | **3.5** | **3.1** | **3.0** | **3.7** | **2.3** |
| **Variance** | **2.9** | **12.4** | **9.8** | **9.3** | **13.7** | **5.4** |
| **Mean & CI** | **36.8±1.0** | **26.0±2.2** | **70.0±1.9** | **32.2±1.9** | **47.8±2.3** | **8.2±1.4** |

*Table F.22: Predictive performance of the See5 un-boosted model for Wine quality*

| Test set | Accuracy on all classes | See5 un-boosted OVA model TPRATE% for class: | | | | |
|---|---|---|---|---|---|---|
| | | 4 | 5 | 6 | 7 | 8 |
| 1 | 34 | 42 | 64 | 14 | 36 | 14 |
| 2 | 34.8 | 38 | 68 | 20 | 40 | 8 |
| 3 | 38 | 42 | 70 | 12 | 48 | 18 |
| 4 | 29.6 | 26 | 68 | 6 | 42 | 6 |
| 5 | 36.4 | 48 | 70 | 10 | 42 | 12 |
| 6 | 32 | 34 | 66 | 10 | 40 | 10 |
| 7 | 36 | 46 | 58 | 14 | 46 | 16 |
| 8 | 38 | 46 | 60 | 18 | 52 | 14 |
| 9 | 34 | 40 | 58 | 14 | 38 | 20 |
| 10 | 35.6 | 40 | 64 | 16 | 44 | 14 |
| **Mean** | **34.8** | **40.2** | **64.6** | **13.4** | **42.8** | **13.2** |
| **StDev** | **2.6** | **6.5** | **4.6** | **4.1** | **4.8** | **4.3** |
| **Variance** | **6.8** | **42.2** | **21.4** | **16.9** | **23.3** | **18.8** |
| **Mean & CI** | **34.8±1.6** | **40.2±4.0** | **64.6±2.9** | **13.4±2.6** | **42.8±3.0** | **13.2±2.7** |

*Table F.23: Predictive performance of the See5 boosted model for Wine quality*

| Test set | Accuracy on all classes | See5 boosted OVA model TPRATE% for class: | | | | |
|---|---|---|---|---|---|---|
| | | 4 | 5 | 6 | 7 | 8 |
| 1 | 36.4 | 42 | 68 | 14 | 42 | 16 |
| 2 | 36 | 38 | 72 | 16 | 46 | 8 |
| 3 | 37.6 | 42 | 74 | 6 | 48 | 18 |
| 4 | 31.2 | 26 | 72 | 4 | 46 | 8 |
| 5 | 36.4 | 48 | 72 | 6 | 42 | 14 |
| 6 | 33.2 | 34 | 66 | 10 | 44 | 12 |
| 7 | 36.4 | 46 | 62 | 8 | 50 | 16 |
| 8 | 38.8 | 46 | 64 | 14 | 56 | 14 |
| 9 | 35.2 | 40 | 62 | 12 | 42 | 20 |
| 10 | 34.8 | 40 | 66 | 8 | 46 | 14 |
| **Mean** | **35.6** | **40.2** | **67.8** | **9.8** | **46.2** | **14.0** |
| **StDev** | **2.2** | **6.5** | **4.5** | **4.0** | **4.4** | **3.9** |
| **Variance** | **4.7** | **42.2** | **20.0** | **16.4** | **19.1** | **15.1** |
| **Mean & CI** | **35.6±1.3** | **40.2±4.0** | **67.8±2.8** | **9.8±2.5** | **46.2±2.7** | **14.0±2.4** |

*Table F.24: Predictive performance of the See5 pVn model for Wine quality*

| Test set | Accuracy on all classes | See5 pVn model TPRATE% for class: | | | | |
|---|---|---|---|---|---|---|
| | | 4 | 5 | 6 | 7 | 8 |
| 1 | 42 | 34 | 56 | 44 | 60 | 16 |
| 2 | 39.6 | 28 | 54 | 42 | 64 | 10 |
| 3 | 42.4 | 40 | 58 | 36 | 64 | 14 |
| 4 | 38 | 26 | 58 | 38 | 58 | 10 |
| 5 | 40.8 | 38 | 56 | 42 | 54 | 14 |
| 6 | 39.2 | 38 | 50 | 42 | 50 | 16 |
| 7 | 42.8 | 34 | 62 | 48 | 54 | 16 |
| 8 | 41.2 | 38 | 50 | 40 | 64 | 14 |
| 9 | 38.8 | 32 | 46 | 42 | 56 | 18 |
| 10 | 40.8 | 36 | 60 | 32 | 60 | 16 |
| **Mean** | **40.6** | **34.4** | **55.0** | **40.6** | **58.4** | **14.4** |
| **StDev** | **1.6** | **4.6** | **5.0** | **4.4** | **4.9** | **2.6** |
| **Variance** | **2.6** | **21.2** | **25.1** | **19.6** | **23.8** | **6.9** |
| **Mean & CI** | **40.6±1.0** | **34.4±2.9** | **55.0±3.1** | **40.6±2.7** | **58.4±3.0** | **14.4±1.6** |

*Table F.25: Statistical tests for 5NN single and aggregate model comparison for wine quality*

| Wine quality white: 5NN models | | | | | | |
|---|---|---|---|---|---|---|
| Group names and mean accuracy /TPRATE:10 test sets | | Student's paired t-test (9 df) | | | Performance improvement measures | |
| Group A aggregate model | Group B single model | 95% CI of mean difference | P value (2 tail) | Group A better than Group B? | Diff(A,B)% | Ratio(A,B) |
| OVA un-boosted All classes-A (32.2 ± 1.2) | All classes-S (31.6 ± 1.3) | [-1.2, 2.2] | 0.511 | no | 0.5 | 0.01 |
| OVA un-boosted Class4-A (12.6 ± 2.1) | Class4-S (11.6 ± 2.2) | [-0.9, 2.9] | 0.273 | no | 1.0 | 0.01 |
| OVA un-boosted Class5-A 59.0 ± 2.7) | Class5-S (54.8 ± 2.9) | [-0.3, 8.7] | 0.066 | yes | 4.2 | 0.09 |
| OVA un-boosted Class6-A (29.9 ± 2.3) | Class6-S (31.4 ± 3.3) | [-6.2, 2.2] | 0.311 | no | -2.0 | -0.03 |
| OVA un-boosted Class7-A (49.8 ± 3.1) | Class7-S (49.4 ± 2.8) | [-4.1, 4.9] | 0.846 | no | 0.4 | 0.01 |
| OVA un-boosted Class8-A (10.0 ± 1.9) | Class8-S (10.2 ± 2.0) | [-1.3, 0.9] | 0.678 | no | -0.2 | 0.00 |
| | | | | | | |
| OVA boosted All classes-A (33.6 ± 1.5) | All classes-S (31.6 ± 1.3) | [0.1, 3.7] | 0.041 | yes | 1.9 | 0.03 |
| OVA boosted Class4-A 13.6 ± 2.1) | Class4-S (11.6 ± 2.2) | [0.3, 3.7] | 0.023 | yes | 2.0 | 0.02 |
| OVA boosted Class5-A (65.6 ± 1.7) | Class5-S (54.8 ± 2.9) | [6.9, 14.7] | 0.000 | yes | 10.8 | 0.24 |
| OVA boosted Class6-A (25.0 ± 3.9) | Class6-S (31.4 ± 3.3) | [-11.8, -1.0] | 0.025 | no | -6.4 | -0.09 |
| OVA boosted Class7-A (52.2 ± 3.3) | Class7-S (49.4 ± 2.8) | [-1.6, 7.3] | 0.191 | no | 2.8 | 0.06 |
| OVA un-boosted Class8-A (11.4 ± 2.2) | Class8-S (10.2 ± 2.0) | [-0.2, 2.9] | 0.081 | yes | 1.2 | 0.01 |
| | | | | | | |
| pVn All classes-A (34.6 ± 1.5) | All classes-S (31.6 ± 1.3) | [1.0, 4.9] | 0.008 | yes | 2.9 | 0.04 |
| pVn Class4-A (11.4 ± 2.6) | Class4-S (11.6 ± 2.2) | [-2.7, 2.3] | 0.859 | no | -0.2 | 0.00 |
| pVn Class5-A (55.0 ± 3.7) | Class5-S (54.8 ± 2.9) | -5.6, 6.0] | 0.939 | no | 0.2 | 0.00 |
| pVn Class6-A (51.6 ± 3.3) | Class6-S (31.4 ± 3.3) | [14.3, 26.1] | 0.000 | yes | 20.2 | 0.29 |
| pVn Class7-A (44.2 ± 4.7) | Class7-S (49.4 ± 2.8) | [-11.0, 0.6] | 0.074 | no | -5.2 | -0.10 |
| pVn Class8-A (10.6 ± 1.9) | Class8-S (10.2 ± 2.0) | [-0.2, 1.0] | 0.168 | no | 0.4 | 0.00 |

Table F.26: Statistical tests for See5 single and aggregate model comparison for wine quality

| **Wine quality white: See5 models** | | | | | | |
|---|---|---|---|---|---|---|
| Group names and mean accuracy /TPRATE:10 test sets | | Student's paired t-test (9 df) | | | Performance improvement measures | |
| Group A aggregate model | Group B single model | 95% CI of mean difference | P value (2 tail) | Group A better than Group B? | Diff(A,B)% | Ratio(A,B) |
| OVA un-boosted All classes-A (34.8 ± 1.6) | All classes-S (36.8 ± 1.0) | [-3.7, -0.2] | 0.034 | no | -1.9 | -0.03 |
| OVA un-boosted Class4-A (40.2 ± 4.0) | Class4-S (26.0 ± 2.2) | [10.3, 18.1] | 0.000 | yes | 14.2 | 0.19 |
| OVA un-boosted Class5-A 64.6 ± 2.9) | Class5-S (70.0 ± 1.9) | [-9.1, -1.7] | 0.009 | no | -5.4 | -0.18 |
| OVA un-boosted Class6-A (13.4 ± 2.9) | Class6-S (32.2 ± 1.9) | [-20.8, -16.8] | 0.000 | no | -18.8 | -0.28 |
| OVA un-boosted Class7-A (42.8 ± 3.8) | Class7-S (47.8 ± 2.8) | [-10.3, 0.3] | 0.062 | no | -5.0 | -0.10 |
| OVA un-boosted Class8-A (13.2 ± 2.7) | Class8-S (8.2 ± 1.4) | [0.7, 9.1] | 0.028 | yes | 5.0 | 0.05 |
| | | | | | | |
| OVA boosted All classes-A (35.6 ± 1.3) | All classes-S (36.8 ± 1.0) | [-2.4, 0.1] | 0.062 | no | -1.2 | -0.02 |
| OVA boosted Class4-A (40.2 ± 4.0) | Class4-S (26.0 ± 2.2) | [10.3, 18.1] | 0.000 | yes | 14.2 | 0.19 |
| OVA boosted Class5-A (67.8 ± 2.8) | Class5-S (70.0 ± 1.9) | [-6.0, 1.6] | 0.227 | no | -2.2 | -0.07 |
| OVA boosted Class6-A (9.8 ± 2.5) | Class6-S (32.2 ± 1.9) | [-24.8, -20.0] | 0.000 | no | -22.4 | -0.33 |
| OVA boosted Class7-A (46.2 ± 2.7) | Class7-S (47.8 ± 2.8) | [-6.5, 3.3] | 0.475 | no | -1.6 | -0.03 |
| OVA un-boosted Class8-A (14.0 ± 2.4) | Class8-S (8.2 ± 1.4) | [1.8, 9.7] | 0.100 | yes | 5.8 | 0.06 |
| | | | | | | |
| pVn All classes-A (40.6 ± 1.0) | All classes-S (36.8 ± 1.0) | [2.4, 5.1] | 0.000 | yes | 3.8 | 0.06 |
| pVn Class4-A (34.4 ± 2.9) | Class4-S (26.0 ± 2.2) | [5.8, 11.0] | 0.000 | yes | 8.4 | 0.11 |
| pVn Class5-A (55.0 ± 3.1) | Class5-S (70.0 ± 1.9) | [-18.9, -11.1] | 0.000 | no | -15.0 | -0.50 |
| pVn Class6-A (40.6 ± 2.7) | Class6-S (32.2 ± 1.9) | [5.6, 11.2] | 0.000 | yes | 8.4 | 0.12 |
| pVn Class7-A (58.4 ± 3.0) | Class7-S (47.8 ± 2.8) | [7.0, 14.2] | 0.000 | yes | 10.6 | 0.20 |
| pVn Class8-A (14.4 ± 1.6] | Class8-S (8.2 ± 1.4) | [2.9, 9.1] | 0.002 | yes | 6.2 | 0.07 |

# Appendix G

# ROC analysis details

The computational method for the AUC and the detailed results for ROC analysis are provided in this appendix. The ROC analysis that was conducted for the experiments was discussed in chapter 9. The method used to compute the Area Under the ROC curve (AUC) is depicted in figure G.1 and table G.1. Figure G.1 shows a ROC curve created with three points corresponding to three threshold points $\lambda_1, \lambda_2$ and $\lambda_3$. The x-axis and y-axis respectively represent the FPRATE and TPRATE of a probabilistic classifier. Threshold averaging was used for the computation of the AUC. Recall from chapter 9 that for threshold averaging, the co-ordinates of each point on the ROC curve are obtained by computing the mean FPRATE (x co-ordinate) and mean TPRATE (y co-ordinate) for one threshold value $\lambda_i$. The mean FPRATE and TPRATE values were computed for 10 test sets. The areas of regions A1 to A7 were used to compute the AUC as shown in table G.1.

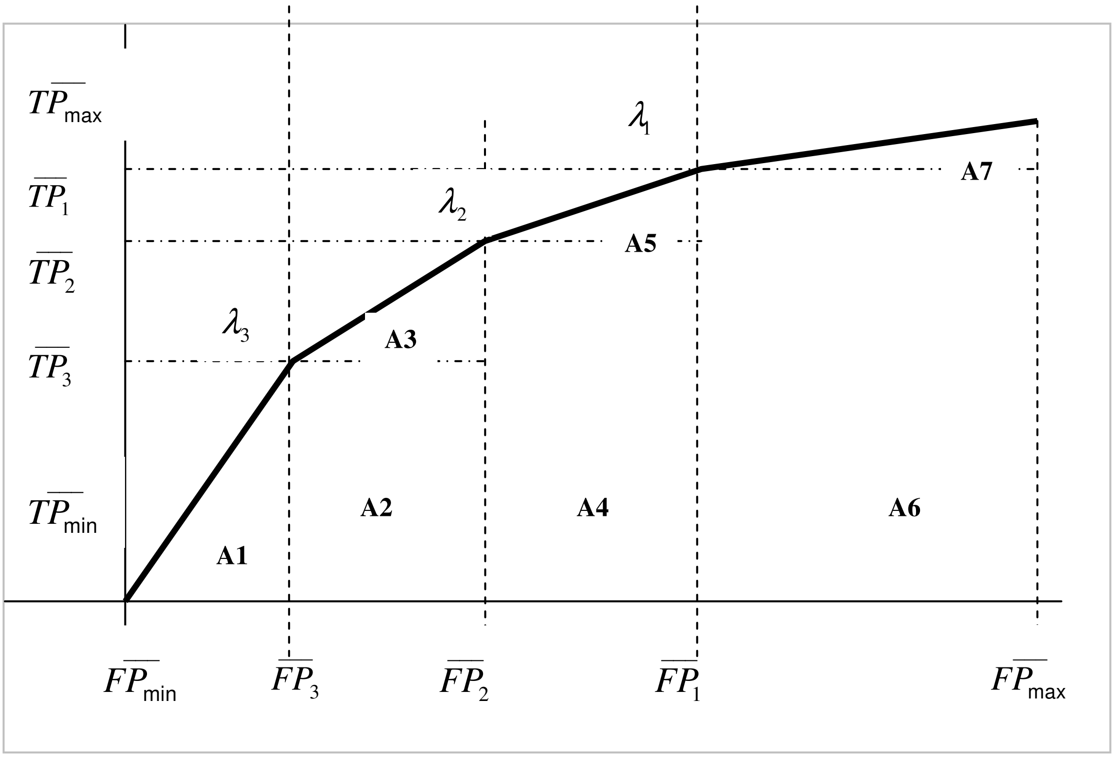


*Figure G.1: Areas of the ROC plane used to compute the AUC*

*Table G.1: Method used for the computation of the AUC for probabilistic classifiers*

| Area code | Computation |
|---|---|
| A1 | ½ * (FP3 * TP3) |
| A2 | (FP2 – FP3) * TP3 |
| A3 | ½ * (FP2 – FP3) * (TP2 – TP3) |
| A4 | (FP1 – FP2) * TP2 |
| A5 | ½ * (FP1 – FP2) * (TP1 - TP2) |
| A6 | (FPmax - FP1) * TP1 |
| A7 | ½ * (FPmax - FP1) * (TPmax – TP1) |
| TOTAL | A1 + A2 + A3 + A4 + A5 + A6 + A7 |
| $AUC_{above}$ | (TOTAL – area under 45deg line) |
| AUC | TOTAL |

Tables G.2 to G.7 provide the details of the FPRATE values (FP1, FP2, FP3) and TPRATE values (TP1, TP2, TP3) and AUC values for the forest cover type, KDD Cup 1999 and wine quality datasets. The AUC is the area between the x-axis, y-axis and ROC curve. $AUC_{above}$ is the area between the 45 degree line and the ROC curve. The threshold values of 0.6, 0.8 and 1.0 for the 5NN classifiers correspond to the number of nearest neighbours (3, 4, 5) used by the 5NN algorithm to determine the winning class. The threshold values of 0.5, 0.75 and 1.0 were used for the See5 classifiers. The positive class column represents a *one-vs-rest* classifier which predicts the indicated class as the positive class and all the other classes as negative classes.

*Table G.2: One-vs-rest AUC for the 5NN forest cover type models*

| 5NN forest cover type models: TPRATE, FPRATE, AUC and Mean AUC | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean values for thresholds | | | | | | | |
| | | $\lambda_1 = 0.6$ | | $\lambda_2 = 0.8$ | | $\lambda_3 = 1.0$ | | | |
| Model | Positive class | FP1 | TP1 | FP2 | TP2 | FP3 | TP3 | $AUC$ | $AUC_{above}$ |
| single 5NN | 1 | 0.04 | 0.62 | 0.02 | 0.37 | 0.00 | 0.17 | 0.79 | 0.29 |
| | 2 | 0.03 | 0.48 | 0.01 | 0.27 | 0.00 | 0.09 | 0.73 | 0.23 |
| | 3 | 0.03 | 0.51 | 0.01 | 0.32 | 0.00 | 0.15 | 0.75 | 0.25 |
| | 4 | 0.03 | 0.92 | 0.02 | 0.78 | 0.01 | 0.53 | 0.95 | 0.45 |
| | 5 | 0.03 | 0.88 | 0.02 | 0.78 | 0.01 | 0.48 | 0.93 | 0.43 |
| | 6 | 0.05 | 0.70 | 0.02 | 0.44 | 0.01 | 0.18 | 0.83 | 0.33 |
| | 7 | 0.03 | 0.95 | 0.01 | 0.82 | 0.01 | 0.64 | 0.97 | 0.47 |
| | | | | | | **Mean:** | | **0.85** | **0.35** |
| OVA unboosted 5NN | 1 | 0.03 | 0.70 | 0.03 | 0.69 | 0.03 | 0.58 | 0.83 | 0.33 |
| | 2 | 0.03 | 0.58 | 0.03 | 0.57 | 0.02 | 0.49 | 0.78 | 0.28 |
| | 3 | 0.03 | 0.72 | 0.03 | 0.72 | 0.02 | 0.60 | 0.85 | 0.35 |
| | 4 | 0.02 | 0.90 | 0.02 | 0.87 | 0.01 | 0.67 | 0.94 | 0.44 |
| | 5 | 0.04 | 0.96 | 0.04 | 0.96 | 0.03 | 0.89 | 0.96 | 0.46 |
| | 6 | 0.05 | 0.81 | 0.05 | 0.80 | 0.03 | 0.67 | 0.88 | 0.38 |
| | 7 | 0.03 | 0.97 | 0.03 | 0.97 | 0.02 | 0.91 | 0.97 | 0.47 |
| | | | | | | **Mean:** | | **0.89** | **0.39** |
| OVA boosted 5NN | 1 | 0.03 | 0.70 | 0.03 | 0.69 | 0.03 | 0.58 | 0.83 | 0.33 |
| | 2 | 0.03 | 0.62 | 0.03 | 0.60 | 0.02 | 0.51 | 0.80 | 0.30 |
| | 3 | 0.03 | 0.71 | 0.03 | 0.71 | 0.02 | 0.61 | 0.84 | 0.34 |
| | 4 | 0.02 | 1.00 | 0.02 | 1.00 | 0.01 | 1.00 | 0.99 | 0.49 |
| | 5 | 0.04 | 0.97 | 0.03 | 0.94 | 0.02 | 0.82 | 0.97 | 0.47 |
| | 6 | 0.04 | 0.78 | 0.04 | 0.75 | 0.03 | 0.63 | 0.87 | 0.37 |
| | 7 | 0.03 | 0.97 | 0.03 | 0.97 | 0.02 | 0.91 | 0.97 | 0.47 |
| | | | | | | **Mean:** | | **0.90** | **0.40** |
| pVn 5NN | 1 | 0.05 | 0.68 | 0.03 | 0.62 | 0.01 | 0.36 | 0.82 | 0.32 |
| | 2 | 0.04 | 0.57 | 0.03 | 0.50 | 0.02 | 0.30 | 0.77 | 0.27 |
| | 3 | 0.04 | 0.65 | 0.03 | 0.52 | 0.01 | 0.34 | 0.81 | 0.31 |
| | 4 | 0.03 | 0.97 | 0.02 | 0.83 | 0.01 | 0.68 | 0.98 | 0.48 |
| | 5 | 0.04 | 0.94 | 0.03 | 0.89 | 0.02 | 0.79 | 0.96 | 0.46 |
| | 6 | 0.05 | 0.75 | 0.03 | 0.65 | 0.01 | 0.39 | 0.86 | 0.36 |
| | 7 | 0.02 | 0.93 | 0.01 | 0.67 | 0.01 | 0.67 | 0.96 | 0.46 |
| | | | | | | **Mean:** | | **0.88** | 0.38 |

*Table G.3: One-vs-rest AUC for the 5NN KDD Cup 1999 models*

| 5NN KDD Cup 1999 models: TPRATE, FPRATE, AUC and Mean AUC | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | Positive class | Mean values for thresholds | | | | | | $AUC$ | $AUC_{above}$ |
| | | $\lambda_1 = 0.6$ | | $\lambda_2 = 0.8$ | | $\lambda_3 = 1.0$ | | | |
| | | FP1 | TP1 | FP2 | TP2 | FP3 | TP3 | | |
| single 5NN | NORM | 0.22 | 0.84 | 0.13 | 0.84 | 0.11 | 0.80 | 0.86 | 0.36 |
| | R2L | 0.06 | 0.65 | 0.05 | 0.60 | 0.04 | 0.53 | 0.80 | 0.30 |
| | DOS | 0.01 | 0.66 | 0.01 | 0.63 | 0.01 | 0.61 | 0.83 | 0.33 |
| | PROBE | 0.09 | 0.96 | 0.09 | 0.96 | 0.07 | 0.93 | 0.94 | 0.44 |
| | U2R | 0.01 | 0.31 | 0.01 | 0.26 | 0.01 | 0.20 | 0.65 | 0.15 |
| | | | | | | **Mean:** | | **0.82** | **0.32** |
| OVA unboosted 5NN | NORM | 0.14 | 0.92 | 0.13 | 0.92 | 0.10 | 0.92 | 0.91 | 0.41 |
| | R2L | 0.07 | 0.65 | 0.07 | 0.62 | 0.06 | 0.57 | 0.79 | 0.29 |
| | DOS | 0.00 | 0.66 | 0.00 | 0.66 | 0.00 | 0.65 | 0.83 | 0.33 |
| | PROBE | 0.08 | 0.95 | 0.08 | 0.95 | 0.08 | 0.95 | 0.94 | 0.44 |
| | U2R | 0.01 | 0.43 | 0.01 | 0.43 | 0.01 | 0.31 | 0.71 | 0.21 |
| | | | | | | **Mean:** | | **0.83** | **0.33** |
| OVA boosted 5NN | NORM | 0.15 | 0.92 | 0.13 | 0.92 | 0.10 | 0.92 | 0.91 | 0.41 |
| | R2L | 0.07 | 0.61 | 0.06 | 0.59 | 0.05 | 0.52 | 0.77 | 0.27 |
| | DOS | 0.00 | 0.66 | 0.00 | 0.66 | 0.00 | 0.66 | 0.83 | 0.33 |
| | PROBE | 0.08 | 0.95 | 0.08 | 0.95 | 0.08 | 0.95 | 0.94 | 0.44 |
| | U2R | 0.01 | 0.40 | 0.01 | 0.40 | 0.01 | 0.29 | 0.70 | 0.20 |
| | | | | | | **Mean:** | | **0.83** | **0.33** |
| pVn 5NN | NORM | 0.16 | 0.99 | 0.15 | 0.99 | 0.12 | 0.98 | 0.93 | 0.43 |
| | R2L | 0.07 | 0.81 | 0.06 | 0.81 | 0.06 | 0.78 | 0.88 | 0.38 |
| | DOS | 0.00 | 0.97 | 0.00 | 0.97 | 0.00 | 0.72 | 0.98 | 0.48 |
| | PROBE | 0.00 | 0.98 | 0.00 | 0.98 | 0.00 | 0.98 | 0.99 | 0.49 |
| | U2R | 0.01 | 0.26 | 0.01 | 0.20 | 0.00 | 0.05 | 0.63 | 0.13 |
| | | | | | | **Mean:** | | **0.88** | **0.33** |

*Table G.4: One-vs-rest AUC for the 5NN Wine quality models*

| 5NN Wine quality (white) models: Mean TPRATE, mean FPRATE, AUC and Mean AUC | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean values for thresholds | | | | | | | |
| | | $\lambda_1 = 0.6$ | | $\lambda_2 = 0.8$ | | $\lambda_3 = 1.0$ | | | |
| Model | positive class | FP1 | TP1 | FP2 | TP2 | FP3 | TP3 | $AUC$ | $AUC_{above}$ |
| single 5NN | 4 | 0.04 | 0.12 | 0.02 | 0.08 | 0.01 | 0.04 | 0.54 | 0.04 |
| | 5 | 0.20 | 0.48 | 0.10 | 0.29 | 0.04 | 0.11 | 0.65 | 0.15 |
| | 6 | 0.17 | 0.22 | 0.04 | 0.08 | 0.01 | 0.01 | 0.53 | 0.03 |
| | 7 | 0.23 | 0.42 | 0.10 | 0.16 | 0.04 | 0.03 | 0.59 | 0.09 |
| | 8 | 0.02 | 0.10 | 0.01 | 0.07 | 0.00 | 0.03 | 0.54 | 0.04 |
| | | | | | | **Mean** | **AUC:** | **0.57** | **0.07** |
| OVA un-boosted 5NN | 4 | 0.05 | 0.13 | 0.05 | 0.13 | 0.04 | 0.09 | 0.54 | 0.04 |
| | 5 | 0.27 | 0.59 | 0.25 | 0.55 | 0.12 | 0.34 | 0.67 | 0.17 |
| | 6 | 0.22 | 0.29 | 0.19 | 0.26 | 0.11 | 0.16 | 0.54 | 0.04 |
| | 7 | 0.28 | 0.50 | 0.25 | 0.42 | 0.17 | 0.33 | 0.61 | 0.11 |
| | 8 | 0.02 | 0.10 | 0.02 | 0.10 | 0.02 | 0.10 | 0.54 | 0.04 |
| | | | | | | **Mean** | **AUC:** | **0.58** | **0.08** |
| OVA boosted 5NN | 4 | 0.05 | 0.14 | 0.05 | 0.14 | 0.05 | 0.10 | 0.54 | 0.04 |
| | 5 | 0.31 | 0.66 | 0.29 | 0.59 | 0.13 | 0.35 | 0.68 | 0.18 |
| | 6 | 0.13 | 0.25 | 0.09 | 0.20 | 0.02 | 0.08 | 0.56 | 0.06 |
| | 7 | 0.29 | 0.52 | 0.27 | 0.48 | 0.17 | 0.35 | 0.62 | 0.12 |
| | 8 | 0.03 | 0.11 | 0.03 | 0.11 | 0.02 | 0.11 | 0.54 | 0.04 |
| | | | | | | **Mean** | **AUC:** | **0.59** | **0.09** |
| pVn 5NN | 4 | 0.05 | 0.11 | 0.04 | 0.09 | 0.02 | 0.02 | 0.53 | 0.03 |
| | 5 | 0.23 | 0.53 | 0.15 | 0.39 | 0.04 | 0.16 | 0.66 | 0.16 |
| | 6 | 0.27 | 0.50 | 0.17 | 0.32 | 0.04 | 0.12 | 0.62 | 0.12 |
| | 7 | 0.22 | 0.44 | 0.15 | 0.28 | 0.06 | 0.08 | 0.60 | 0.10 |
| | 8 | 0.02 | 0.11 | 0.02 | 0.09 | 0.01 | 0.06 | 0.55 | 0.05 |
| | | | | | | **Mean** | **AUC:** | **0.59** | **0.09** |

*Table G.5: One-vs-rest AUC for the See5 forest cover type models*

| See5 forest cover type models: TPRATE, FPRATE, AUC and Mean AUC | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean values for thresholds | | | | | | | |
| | | $\lambda_1 = 0.5$ | | $\lambda_2 = 0.75$ | | $\lambda_3 = 1.0$ | | | |
| Model | Positive class | FP1 | TP1 | FP2 | TP2 | FP3 | TP3 | $AUC$ | $AUC_{above}$ |
| single See5 | 1 | 0.03 | 0.57 | 0.01 | 0.28 | 0.00 | 0.04 | 0.77 | 0.27 |
| | 2 | 0.06 | 0.63 | 0.03 | 0.39 | 0.00 | 0.04 | 0.79 | 0.29 |
| | 3 | 0.03 | 0.61 | 0.01 | 0.41 | 0.00 | 0.04 | 0.79 | 0.29 |
| | 4 | 0.03 | 0.94 | 0.02 | 0.90 | 0.00 | 0.08 | 0.96 | 0.46 |
| | 5 | 0.03 | 0.86 | 0.02 | 0.77 | 0.00 | 0.00 | 0.92 | 0.42 |
| | 6 | 0.05 | 0.78 | 0.03 | 0.60 | 0.00 | 0.05 | 0.87 | 0.37 |
| | 7 | 0.03 | 0.96 | 0.02 | 0.85 | 0.01 | 0.03 | 0.97 | 0.47 |
| | | | | | | **Mean:** | | **0.87** | **0.37** |
| OVA unboosted 5NNSee5 | 1 | 0.05 | 0.61 | 0.05 | 0.60 | 0.00 | 0.01 | 0.78 | 0.28 |
| | 2 | 0.05 | 0.50 | 0.05 | 0.50 | 0.00 | 0.00 | 0.72 | 0.22 |
| | 3 | 0.04 | 0.64 | 0.04 | 0.62 | 0.00 | 0.02 | 0.80 | 0.30 |
| | 4 | 0.01 | 0.87 | 0.01 | 0.85 | 0.00 | 0.00 | 0.93 | 0.43 |
| | 5 | 0.04 | 0.94 | 0.04 | 0.94 | 0.00 | 0.01 | 0.95 | 0.45 |
| | 6 | 0.07 | 0.79 | 0.07 | 0.79 | 0.00 | 0.08 | 0.86 | 0.36 |
| | 7 | 0.03 | 0.93 | 0.03 | 0.93 | 0.00 | 0.00 | 0.95 | 0.45 |
| | | | | | | **Mean:** | | **0.86** | **0.36** |
| OVA boosted See5 | 1 | 0.03 | 0.63 | 0.02 | 0.52 | 0.00 | 0.04 | 0.80 | 0.30 |
| | 2 | 0.07 | 0.67 | 0.07 | 0.62 | 0.01 | 0.01 | 0.80 | 0.30 |
| | 3 | 0.02 | 0.63 | 0.02 | 0.62 | 0.00 | 0.08 | 0.80 | 0.30 |
| | 4 | 0.01 | 0.95 | 0.01 | 0.94 | 0.00 | 0.04 | 0.97 | 0.47 |
| | 5 | 0.04 | 0.87 | 0.04 | 0.87 | 0.00 | 0.09 | 0.92 | 0.42 |
| | 6 | 0.04 | 0.76 | 0.04 | 0.76 | 0.00 | 0.05 | 0.86 | 0.36 |
| | 7 | 0.01 | 0.98 | 0.01 | 0.97 | 0.00 | 0.22 | 0.98 | 0.48 |
| | | | | | | **Mean:** | | **0.88** | **0.38** |
| pVn See5 | 1 | 0.04 | 0.65 | 0.02 | 0.54 | 0.00 | 0.08 | 0.81 | 0.31 |
| | 2 | 0.06 | 0.65 | 0.05 | 0.61 | 0.00 | 0.04 | 0.80 | 0.30 |
| | 3 | 0.04 | 0.72 | 0.03 | 0.68 | 0.00 | 0.09 | 0.84 | 0.34 |
| | 4 | 0.01 | 0.95 | 0.01 | 0.89 | 0.00 | 0.01 | 0.97 | 0.47 |
| | 5 | 0.02 | 0.89 | 0.02 | 0.81 | 0.00 | 0.00 | 0.93 | 0.43 |
| | 6 | 0.05 | 0.82 | 0.04 | 0.78 | 0.00 | 0.12 | 0.89 | 0.39 |
| | 7 | 0.02 | 0.92 | 0.01 | 0.88 | 0.00 | 0.03 | 0.95 | 0.45 |
| | | | | | | **Mean:** | | **0.88** | **0.38** |

Table G.6: One-vs-rest AUC for the See5 KDD Cup 1999 models

| See5 KDD Cup 1999 models: TPRATE, FPRATE, AUC and Mean AUC | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean values for thresholds | | | | | | | |
| | | $\lambda_1 = 0.5$ | | $\lambda_2 = 0.75$ | | $\lambda_3 = 1.0$ | | | |
| Model | Positive class | FP1 | TP1 | FP2 | TP2 | FP3 | TP3 | $AUC$ | $AUC_{above}$ |
| single See5 | NORM | 0.22 | 0.86 | 0.22 | 0.86 | 0.02 | 0.63 | 0.88 | 0.38 |
| | R2L | 0.02 | 0.38 | 0.02 | 0.38 | 0.00 | 0.12 | 0.68 | 0.18 |
| | DOS | 0.02 | 0.82 | 0.02 | 0.82 | 0.02 | 0.82 | 0.90 | 0.40 |
| | PROBE | 0.04 | 0.36 | 0.04 | 0.36 | 0.02 | 0.36 | 0.67 | 0.17 |
| | U2R | 0.16 | 0.77 | 0.16 | 0.77 | 0.00 | 0.00 | 0.81 | 0.31 |
| | | | | | | **Mean:** | | **0.79** | **0.29** |
| OVA unboosted See5 | NORM | 0.11 | 0.98 | 0.11 | 0.98 | 0.10 | 0.98 | 0.94 | 0.44 |
| | R2L | 0.09 | 0.34 | 0.09 | 0.34 | 0.06 | 0.04 | 0.62 | 0.12 |
| | DOS | 0.00 | 0.50 | 0.00 | 0.50 | 0.00 | 0.01 | 0.75 | 0.25 |
| | PROBE | 0.10 | 0.88 | 0.10 | 0.88 | 0.10 | 0.88 | 0.89 | 0.39 |
| | U2R | 0.01 | 0.46 | 0.01 | 0.46 | 0.00 | 0.00 | 0.73 | 0.23 |
| | | | | | | **Mean:** | | **0.79** | **0.29** |
| OVA boosted See5 | NORM | 0.24 | 0.99 | 0.24 | 0.99 | 0.15 | 0.93 | 0.91 | 0.41 |
| | R2L | 0.02 | 0.24 | 0.02 | 0.24 | 0.00 | 0.01 | 0.61 | 0.11 |
| | DOS | 0.06 | 0.56 | 0.06 | 0.56 | 0.01 | 0.56 | 0.77 | 0.27 |
| | PROBE | 0.08 | 0.89 | 0.08 | 0.89 | 0.08 | 0.89 | 0.91 | 0.41 |
| | U2R | 0.01 | 0.40 | 0.01 | 0.40 | 0.00 | 0.00 | 0.69 | 0.19 |
| | | | | | | **Mean:** | | **0.78** | **0.28** |
| pVn See5 | NORM | 0.20 | 0.98 | 0.20 | 0.98 | 0.07 | 0.41 | 0.90 | 0.40 |
| | R2L | 0.02 | 0.54 | 0.02 | 0.54 | 0.01 | 0.22 | 0.76 | 0.26 |
| | DOS | 0.00 | 0.68 | 0.00 | 0.68 | 0.00 | 0.44 | 0.84 | 0.34 |
| | PROBE | 0.03 | 0.97 | 0.03 | 0.97 | 0.01 | 0.97 | 0.98 | 0.48 |
| | U2R | 0.01 | 0.77 | 0.01 | 0.71 | 0.00 | 0.43 | 0.88 | 0.38 |
| | | | | | | **Mean:** | | **0.87** | **0.37** |

*Table G.7: One-vs-rest AUC for the See5 Wine quality models*

| See5 Wine quality white: TPRATE, FPRATE,auc and MEAN AUC | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Mean values for thresholds | | | | | | | |
| | | $\lambda_1 = 0.5$ | | $\lambda_2 = 0.75$ | | $\lambda_3 = 1.0$ | | | |
| model | positive Class | FP1 | TP1 | FP2 | TP2 | FP3 | TP3 | *AUC* | $AUC_{above}$ |
| single See5 | 4 | 0.04 | 0.26 | 0.04 | 0.26 | 0.00 | 0.01 | 0.61 | 0.11 |
| | 5 | 0.33 | 0.70 | 0.03 | 0.05 | 0.00 | 0.00 | 0.68 | 0.18 |
| | 6 | 0.18 | 0.28 | 0.02 | 0.04 | 0.00 | 0.00 | 0.55 | 0.05 |
| | 7 | 0.19 | 0.48 | 0.05 | 0.14 | 0.00 | 0.00 | 0.64 | 0.14 |
| | 8 | 0.01 | 0.08 | 0.00 | 0.08 | 0.00 | 0.00 | 0.54 | 0.04 |
| | | | | | | **Mean:** | | **0.60** | **0.10** |
| un-boosted OVA See5 | 4 | 0.09 | 0.40 | 0.09 | 0.40 | 0.01 | 0.09 | 0.66 | 0.16 |
| | 5 | 0.30 | 0.65 | 0.30 | 0.65 | 0.02 | 0.01 | 0.67 | 0.17 |
| | **6** | 0.12 | 0.13 | 0.10 | 0.13 | 0.01 | 0.00 | 0.51 | 0.01 |
| | 7 | 0.25 | 0.43 | 0.24 | 0.43 | 0.00 | 0.00 | 0.59 | 0.09 |
| | 8 | 0.03 | 0.13 | 0.03 | 0.13 | 0.00 | 0.00 | 0.55 | 0.05 |
| | | | | | | **Mean:** | | **0.60** | **0.10** |
| boosted OVA See5 | 4 | 0.09 | 0.40 | 0.09 | 0.40 | 0.01 | 0.09 | 0.66 | 0.16 |
| | 5 | 0.33 | 0.68 | 0.31 | 0.68 | 0.02 | 0.01 | 0.68 | 0.18 |
| | 6 | 0.07 | 0.10 | 0.01 | 0.02 | 0.00 | 0.00 | 0.51 | 0.01 |
| | 7 | 0.26 | 0.46 | 0.24 | 0.45 | 0.00 | 0.00 | 0.60 | 0.10 |
| | **8** | 0.03 | 0.14 | 0.03 | 0.13 | 0.00 | 0.00 | 0.56 | 0.06 |
| | | | | | | **Mean:** | | **0.60** | **0.10** |
| pVn See5 | 4 | 0.06 | 0.34 | 0.06 | 0.34 | 0.01 | 0.09 | 0.64 | 0.14 |
| | 5 | 0.19 | 0.55 | 0.14 | 0.48 | 0.00 | 0.00 | 0.69 | 0.19 |
| | 6 | 0.19 | 0.41 | 0.12 | 0.27 | 0.01 | 0.02 | 0.61 | 0.11 |
| | 7 | 0.29 | 0.58 | 0.25 | 0.56 | 0.03 | 0.06 | 0.66 | 0.16 |
| | 8 | 0.02 | 0.14 | 0.02 | 0.14 | 0.01 | 0.00 | 0.56 | 0.06 |
| | | | | | | **Mean:** | | **0.63** | **0.13** |

# Appendix H

# Using statistical and database software to implement dataset selection methods

Recommendations for using database and statistical software for the implementation of dataset selection methods proposed in this thesis were given in chapter 10. Tables H.1 and H.2 provide detailed suggestions for feature selection, training instance selection and model aggregation.

*TableH.1: Suggestions for feature selection using statistical software*

| Feature selection activity | Step for activity | Implementation |
|---|---|---|
| Feature ranking | Generation of probe variables | SPSS, SAS or MS Excel |
| | Sampling | SPSS or SAS |
| | Binarisation of qualitative features and class variable | SPSS, SAS or MS Excel |
| | Measurement of class-feature and feature-feature correlations | Bivariate correlation matrix for quantitative variables |
| | | Pearson's chi-square, SU coefficient, phi and Cramer's V statistics |
| | Computation of mean and 95% CIs of means for correlations | SPSS |
| | Ranking and feature elimination using probes | SPSS or MS Excel |
| Feature subset search | Search for best subset | Specialised code e.g. C++ code |

*Table H.2: Suggestions for OVA and pVn modeling using statistical software*

| Activity | Implementation |
|---|---|
| Sampling for training set to create single model | SPSS or SAS |
| Creation of single model and confusion matrix | SPSS or SAS |
| Dataset partitioning | SPSS, SAS or SQL |
| Sampling from partitions to obtain boosted samples for base model creation | SPSS, SAS |
| Creation of base models | SPSS, SAS or other modelling software |
| Model aggregation | SPSS, SAS or MS Excel or Specialised code e.g. C++ code |

# Appendix I

## Publications and conference presentations

LUTU, P. E. N. & ENGELBRECHT, A. P. (2006) A Comparative Study of Sample Selection methods for Classification. *South African Computer Journal,* 36, 69-85.

LUTU, P. E. N. & ENGELBRECHT, A. P. (2008) A decision rule-based method for feature selection in predictive data mining. Presentation at*: The 18th Triennial Conference of the International Federation of Operational Research Societies (IFORS 2008), Sandton, Johannesburg, July 2008*.

LUTU, P. E. N. & ENGELBRECHT, A. P. (2010) A decision rule-based method for feature selection in predictive data mining. *Expert Systems with Applications,* 37, 602-609.

LUTU, P. E. N. & ENGELBRECHT, A. P. (2010) Using OVA modeling to improve classification performance for large datasets. Submitted to the Journal of Expert Systems With Applications (ESWA).

LUTU, P. E. N. & ENGELBRECHT, A. P. (2010) An algorithm for combining K-Nearest Neighbour base model predictions. Submitted to the Journal of Expert Systems With Applications (ESWA).