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Exploring the Power and Practical Applications of K-Nearest Neighbours (KNN) in Machine Learning

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Abstract:

Machine learning, a cornerstone of artificial intelligence, empowers systems to autonomously acquire knowledge and enhance performance through experiential learning, eliminating the need for explicit programming. This cutting-edge field focuses on equipping computer programs with the ability to access vast datasets and derive intelligent decisions from them. One of the cornerstone algorithms in machine learning, the K-nearest neighbours (KNN) algorithm, is known for its simplicity and effectiveness. KNN leverages the principle of storing all available data points within its training dataset and subsequently classifying new, unclassified cases based on their similarity to the existing dataset. This proximity-based classification approach renders KNN a versatile and intuitive tool with applications spanning diverse domains. This document explores the inner workings of the K-nearest neighbours' algorithm, its practical applications across various domains, and a comprehensive examination of its strengths and limitations. Additionally, it offers insights into practical considerations and best practices for the effective implementation of KNN, illuminating its significance in the continually evolving landscape of machine learning and artificial intelligence.

Introduction:

Machine learning is an integral application of artificial intelligence (AI), empowering systems to autonomously acquire knowledge and enhance their performance through the assimilation of experience, all without the need for explicit programming. At its core, machine learning concentrates on the creation of computer programs that can not only access vast datasets but also adapt and learn from these datasets to make intelligent decisions. One of the fundamental algorithms in machine learning, known for its simplicity and effectiveness, is the K-nearest neighbours (KNN) algorithm. KNN operates on the principle of storing all available data points or cases within its training dataset and subsequently classifying new, unclassified cases based on their similarity to the existing dataset. This approach is rooted in the concept of proximity-based classification, making it a versatile and intuitive method for various applications. In the following sections, we will delve into the mechanics of the K-nearest neighbours' algorithm, explore its applications across different domains, and examine its strengths and limitations. We will also discuss practical

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considerations and best practices for implementing KNN effectively, shedding light on how it contributes to the ever-evolving landscape of machine learning and artificial intelligence. Let's move on to the subsequent sections and content that you'd like to include in your document or presentation.

2.Proposed Algorithm:

Calculate the distance from x to all points in your data.
Sort the points in your data by increasing distance from x.
Predict the majority label of the k closest points.
Note that the value of k effects the results, its ideal to test the model for different values of k for better results and there by a better model.
Data
Glass Identification Database from UCI contains 10 attributes including id. The response is glass type which has 7 discrete values.
Attributes
Id: 1 to 214 (removed from CSV file)
RI: refractive index
Na: Sodium (unit measurement: weight percent in corresponding oxide, as are attributes 4-10)
Mg: Magnesium
Al: Aluminum
Si: Silicon
K: Potassium
Ca: Calcium
Ba: Barium
Fe: Iron
Type of glass: (Class Attribute)
1 - building_windows_float_processed
2 - building_windows_non_float_processed
3 - vehicle_windows_float_processed
4 - vehicle_windows_non_float_processed (none in this database)
5 - containers
6 - tableware
7 - headlamps

2.1 Literature Review:

The provided text appears to be the beginning of a research paper or article authored by Stefan Securing, focusing on conducting content analysis based on literature reviews related to the identification of glass. However, the text also mentions supply chain management

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(SCM) literature reviews and discusses the importance of transparent and systematic procedures in research. It's important to note that the context of the text is somewhat unclear, as it transitions from discussing SCM literature reviews to addressing issues with the quality of literature review processes. If you require assistance with summarizing or expanding on this text, or if you have specific questions related to it, please feel free to provide more context or let me know how I can help further.

2.2 Glass Identification Ieee Review:

The text you provided discusses the content of a research paper or a data analysis project, highlighting the dataset, data preprocessing, and the evaluation methodology employed. It also mentions the use of specific algorithms, C4.5 and K-Means clustering, as well as the handling of missing values in the context of K-Nearest Neighbors (K-NN).Here's a summary:

Dataset Description and Preprocessing:
The paper describes the dataset and its attributes.
Data preprocessing was conducted to check for missing values in the dataset.
The dataset was transformed into ARFF format, a standard representation for datasets with independent, unordered instances.

Evaluation Methodology:

The paper used 10-fold Cross-validation, a common technique for evaluating models. The dataset was split into 10 subsets, with each subset used for testing and the remaining for training.
The use of Cross-validation helps avoid overlapping test sets.
Stratified cross-validation was repeated 10 times to reduce variance and provide an accurate estimate of performance.
Algorithms Used:

C4.5: A decision tree algorithm used for classification.
K-Means Clustering: An unsupervised learning algorithm used to group data based on similarity. It aims to find K clusters in the data.
K-NN (K-Nearest Neighbors): An instance-based learning algorithm that handles missing values differently from C4.5. In K-NN, missing values are treated by comparing the difference between the new instance and existing data points. The majority class of the closest K neighbors is assigned to the new instance.
The text provides an overview of the research's data and methodology, focusing on data preprocessing and the use of machine learning algorithms for analysis.

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2.3 Instance-Based Regression By Partitioning Feature Projections

he text you provided discusses a new instance-based learning method called Regression by Partitioning Feature Projections (RPFP) designed for regression problems with high-dimensional data. This method aims to achieve high accuracy on regression problems, outperforming traditional eager approaches such as MARS, rule-based regression, and regression tree induction systems, as well as the well-known instance-based method K-Nearest Neighbors (KNN). RPFP is particularly effective when dealing with domains that have many missing values in the training data.

Key points highlighted in the text include:

Challenges in Regression Problems: The text points out that while KNN is popular for classification, it doesn't perform as effectively in regression problems.

RPFP Introduction: RPFP is introduced as a new instance-based approach that excels in regression tasks.Handling Interactions: RPFP is unique in its ability to handle interactions among features, making it highly adaptable to real-world regression problems.

Main Effects vs. Interactions: The text acknowledges that in many regression scenarios, main effects are more prevalent than interactions. RPFP is designed to accommodate these situations effectively.

Training Process: RPFP's training process involves storing training data as projections to the features and associating target values with feature dimensions. Instances are sorted based on their feature values for each dimension.

Advantage of Local Weights: RPFP assigns lower local weights to features, making it robust when dealing with target values in query locations.

Handling Irrelevant Features: The text notes that RPFP is not significantly affected by irrelevant features, in contrast to KNN, which struggles with such features.

This text provides an overview of RPFP as a regression method and emphasizes its advantages, particularly in handling interactions and irrelevant features in high-dimensional data.

3. Methodology

The provided text introduces a problem statement and describes a dataset used in a study involving the classification of types of glass. Here's a breakdown:

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3.1 Problem Statement:

The problem is to predict the age of abalone (a type of marine mollusk) from physical measurements. Traditionally, abalone age determination is a time-consuming process that involves cutting the shell, staining it, and counting rings under a microscope.
The objective is to predict age using easier-to-obtain measurements, which might include physical characteristics.Additional information, such as weather patterns and location, could potentially aid in solving this problem.

3.2 Dataset Description:

A comparison test was conducted to evaluate different approaches, including a rule-based system called BEAGLE, the nearest-neighbor (NN) algorithm, and discriminant analysis (DA).
The test involved classifying glass samples as either "float" glass or not.
The results for the number of incorrect answers are provided for each approach.
The study is motivated by its potential application in criminological investigations, where correctly identifying the type of glass left at a crime scene is crucial evidence.
Attribute Description:
The dataset includes the following attributes:

Id number: An identifier from 1 to 214.
RI (refractive index)
Na (Sodium, measured in weight percent in corresponding oxide)
Mg (Magnesium)
Al (Aluminum)
Si (Silicon)
K (Potassium)
Ca (Calcium)
Ba (Barium)
Fe (Iron)
Type of glass: This is the class attribute and includes categories such as building_windows_float_processed, building_windows_non_float_processed, vehicle_windows_float_processed, vehicle_windows_non_float_processed (not present in the database), containers, tableware, and headlamps.
The dataset appears to be used for classification tasks related to the type of glass, with attributes describing its composition and refractive index.

If you have specific questions or need further information about this dataset, please let me know.

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3.3 Preprocessing:

```
nstall.packages('caTools')  #for train and test data split
install.packages('dplyr')    #for Data Manipulation
install.packages('ggplot2')  #for Data Visualization
install.packages('class')    #KNN
install.packages('caret')    #Confusion Matrix
install.packages('corrplot') #Correlation Plot
library(caTools)
library(dplyr)
library(ggplot2)
library(caret)
library(class)
library(corrplot)
glass <- read.csv("https://archive.ics.uci.edu/ml/machine-learning-databases/glass/glass.data",
                  col.names=c("RI","Na","Mg","Al","Si","K","Ca","Ba","Fe","Type"))
standard.features <- scale(glass[,1:9])
standard.features
data <- cbind(standard.features,glass[10])
anyNA(data)
corrplot(cor(data))
set.seed(101)

sample <- sample.split(data$Type,SplitRatio = 0.70)

train <- subset(data,sample==TRUE)

test <- subset(data,sample==FALSE)
predicted.type <- knn(train[1:9],test[1:9],train$Type,k=1)
error <- mean(predicted.type!=test$Type)
predicted.type <- NULL
error.rate <- NULL

for (i in 1:10) {
  predicted.type <- knn(train[1:9],test[1:9],train$Type,k=i)
  error.rate[i] <- mean(predicted.type!=test$Type)

}

knn.error <- as.data.frame(cbind(k=1:10,error.type =error.rate))
ggplot(knn.error,aes(k,error.type))+
  geom_point()+
  geom_line() +
```

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```
  scale_x_continuous(breaks=1:10)+
  theme_bw() +
  xlab("Value of K") +
  ylab('Error')
predicted.type <- knn(train[1:9],test[1:9],train$Type,k=3)
#Error in prediction
error <- mean(predicted.type!=test$Type)
#Confusion Matrix
confusionMatrix(predicted.type,test$Type)
```

4. Results and Discussion

4.1 Preprocessing:

```
## Factor w/ 6 levels "1","2","3","5",..: 1 1 1 1 1 1 1 1 1 1 ...
```

```
set.seed(123)
tree.glass = rpart(Type~., data=train)
print(tree.glass$cptable)
```

```
##         CP nsplit rel error    xerror      xstd
## 1 0.22159091      0 1.0000000 1.0909091 0.05814565
## 2 0.06818182      2 0.5568182 0.6022727 0.06400028
## 3 0.04545455      3 0.4886364 0.6136364 0.06419106
## 4 0.02272727      5 0.3977273 0.4886364 0.06118706
## 5 0.01000000      6 0.3750000 0.5454545 0.06280448
```

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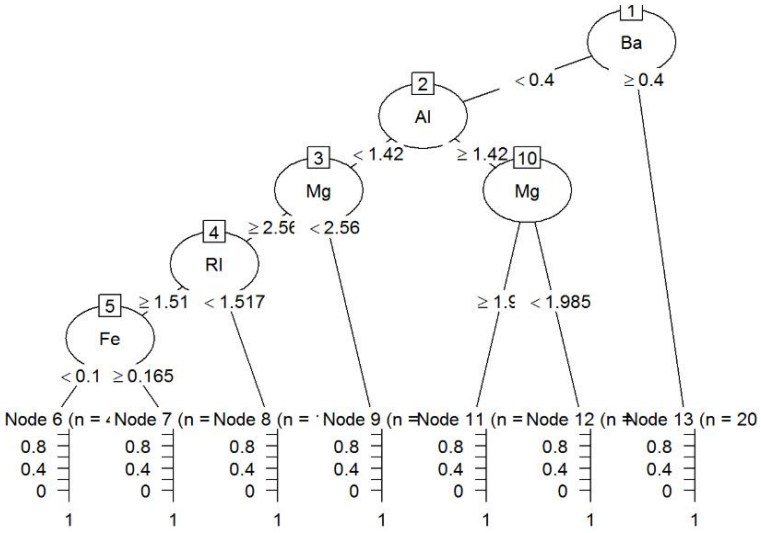
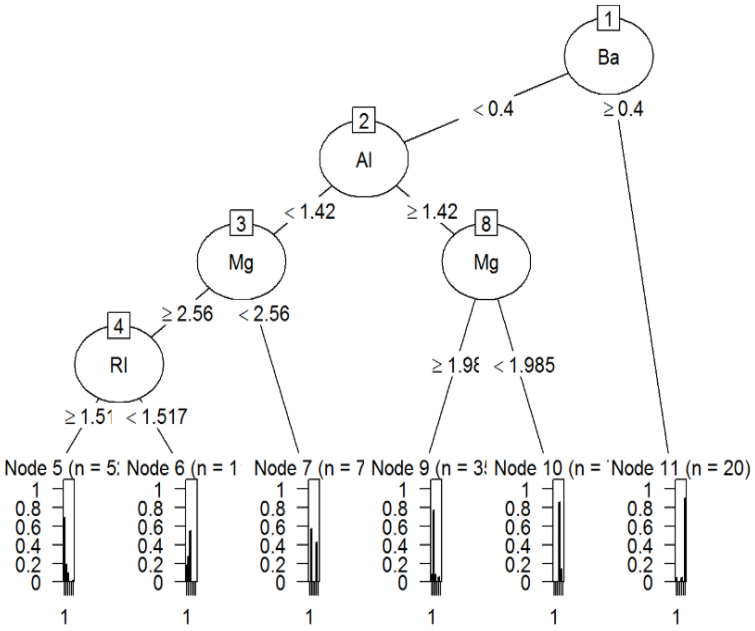
```
cp = min(tree.glass$cptable[4,])
prune.tree.glass = prune(tree.glass, cp = cp)
plot(as.party(tree.glass))
```




```
plot(as.party(prune.tree.glass))
```



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```
rparty.test = predict(prune.tree.glass, newdata=test, type="class")
table(rparty.test, test$Type)
```

```
##
## rparty.test  1  2  3  5  6  7
##           1 24  9  1  0  0  0
##           2  3 19  1  1  1  2
##           3  1  1  1  0  0  0
##           5  0  2  0  5  2  0
##           6  0  0  0  0  0  0
##           7  0  1  0  0  0  8
```

```
(24+19+1+5+0+8)/82
```

```
## [1] 0.695122
```

4.2 Data Analysis:

```
> summary(data)
       X          V1           V2           V3           V4           V5           V6
 Min.   :   1   Female:1307   Min.   :0.075   Min.   :0.0550   Min.   :0.0000   Min.   :0.0020   Min.   :0.0010
 1st Qu.:1045   Infant:1342   1st Qu.:0.450   1st Qu.:0.3500   1st Qu.:0.1150   1st Qu.:0.4415   1st Qu.:0.1860
 Median :2089   Male  :1528   Median :0.545   Median :0.4250   Median :0.1400   Median :0.7995   Median :0.3360
 Mean   :2089                 Mean   :0.524   Mean   :0.4079   Mean   :0.1395   Mean   :0.8287   Mean   :0.3594
 3rd Qu.:3133                 3rd Qu.:0.615   3rd Qu.:0.4800   3rd Qu.:0.1650   3rd Qu.:1.1530   3rd Qu.:0.5020
 Max.   :4177                 Max.   :0.815   Max.   :0.6500   Max.   :1.1300   Max.   :2.8255   Max.   :1.4880
       V7            V8           V9
 Min.   :0.0005   Min.   :0.0015   old  :2406
 1st Qu.:0.0935   1st Qu.:0.1300   Young: 364
 Median :0.1710   Median :0.2340   Adult:1407
 Mean   :0.1806   Mean   :0.2388
 3rd Qu.:0.2530   3rd Qu.:0.3290
 Max.   :0.7600   Max.   :1.0050
```

4.3 Data Splitting:

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```
> train
      X     V1    V2    V3    V4     V5     V6     V7     V8     V9
2     2   Male 0.350 0.265 0.090 0.2255 0.0995 0.0485 0.0700 Adult
3     3 Female 0.530 0.420 0.135 0.6770 0.2565 0.1415 0.2100   Old
4     4   Male 0.440 0.365 0.125 0.5160 0.2155 0.1140 0.1550   Old
6     6 Infant 0.425 0.300 0.095 0.3515 0.1410 0.0775 0.1200 Adult
7     7 Female 0.530 0.415 0.150 0.7775 0.2370 0.1415 0.3300 Young
9     9   Male 0.475 0.370 0.125 0.5095 0.2165 0.1125 0.1650   Old
10   10 Female 0.550 0.440 0.150 0.8945 0.3145 0.1510 0.3200 Young
11   11 Female 0.525 0.380 0.140 0.6065 0.1940 0.1475 0.2100   Old
12   12   Male 0.430 0.350 0.110 0.4060 0.1675 0.0810 0.1350   Old
15   15 Female 0.470 0.355 0.100 0.4755 0.1675 0.0805 0.1850   Old
17   17 Infant 0.355 0.280 0.085 0.2905 0.0950 0.0395 0.1150 Adult
19   19   Male 0.365 0.295 0.080 0.2555 0.0970 0.0430 0.1000 Adult
22   22 Infant 0.380 0.275 0.100 0.2255 0.0800 0.0490 0.0850   Old
26   26 Female 0.560 0.440 0.140 0.9285 0.3825 0.1880 0.3000   Old
27   27 Female 0.580 0.450 0.185 0.9955 0.3945 0.2720 0.2850   Old
29   29   Male 0.605 0.475 0.180 0.9365 0.3940 0.2190 0.2950 Young
30   30   Male 0.575 0.425 0.140 0.8635 0.3930 0.2270 0.2000   Old
31   31   Male 0.580 0.470 0.165 0.9975 0.3935 0.2420 0.3300   Old
32   32 Female 0.680 0.560 0.165 1.6390 0.6055 0.2805 0.4600 Young
34   34 Female 0.680 0.550 0.175 1.7980 0.8150 0.3925 0.4550 Young
35   35 Female 0.705 0.550 0.200 1.7095 0.6330 0.4115 0.4900   Old
36   36   Male 0.465 0.355 0.105 0.4795 0.2270 0.1240 0.1250 Adult
38   38 Female 0.450 0.355 0.105 0.5225 0.2370 0.1165 0.1450 Adult
39   39 Female 0.575 0.445 0.135 0.8830 0.3810 0.2035 0.2600   Old
40   40   Male 0.355 0.290 0.090 0.3275 0.1340 0.0860 0.0900   Old
41   41 Female 0.450 0.335 0.105 0.4250 0.1865 0.0910 0.1150   Old
42   42 Female 0.550 0.425 0.135 0.8515 0.3620 0.1960 0.2700   Old
43   43 Infant 0.240 0.175 0.045 0.0700 0.0315 0.0235 0.0200 Adult
44   44 Infant 0.205 0.150 0.055 0.0420 0.0255 0.0150 0.0120 Adult
45   45 Infant 0.210 0.150 0.050 0.0420 0.0175 0.0125 0.0150 Adult
47   47   Male 0.470 0.370 0.120 0.5795 0.2930 0.2270 0.1400   Old
49   49 Infant 0.325 0.245 0.070 0.1610 0.0755 0.0255 0.0450 Adult
50   50 Female 0.525 0.425 0.160 0.8355 0.3545 0.2135 0.2450   Old
```

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```
> test<-data[-ind,]
> test
```

	X	V1	V2	V3	V4	V5	V6	V7	V8	V9
1	1	Male	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.1500	Young
5	5	Infant	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.0550	Adult
8	8	Female	0.545	0.425	0.125	0.7680	0.2940	0.1495	0.2600	Young
13	13	Male	0.490	0.380	0.135	0.5415	0.2175	0.0950	0.1900	old
14	14	Female	0.535	0.405	0.145	0.6845	0.2725	0.1710	0.2050	old
16	16	Male	0.500	0.400	0.130	0.6645	0.2580	0.1330	0.2400	old
18	18	Female	0.440	0.340	0.100	0.4510	0.1880	0.0870	0.1300	old
20	20	Male	0.450	0.320	0.100	0.3810	0.1705	0.0750	0.1150	old
21	21	Male	0.355	0.280	0.095	0.2455	0.0955	0.0620	0.0750	old
23	23	Female	0.565	0.440	0.155	0.9395	0.4275	0.2140	0.2700	old
24	24	Female	0.550	0.415	0.135	0.7635	0.3180	0.2100	0.2000	old
25	25	Female	0.615	0.480	0.165	1.1615	0.5130	0.3010	0.3050	old
28	28	Male	0.590	0.445	0.140	0.9310	0.3560	0.2340	0.2800	old
33	33	Male	0.665	0.525	0.165	1.3380	0.5515	0.3575	0.3500	Young
37	37	Female	0.540	0.475	0.155	1.2170	0.5305	0.3075	0.3400	Young
46	46	Infant	0.390	0.295	0.095	0.2030	0.0875	0.0450	0.0750	Adult
48	48	Female	0.460	0.375	0.120	0.4605	0.1775	0.1100	0.1500	Adult
51	51	Infant	0.520	0.410	0.120	0.5950	0.2385	0.1110	0.1900	Adult
53	53	Male	0.485	0.360	0.130	0.5415	0.2595	0.0960	0.1600	old
55	55	Male	0.405	0.310	0.100	0.3850	0.1730	0.0915	0.1100	Adult
60	60	Female	0.505	0.400	0.125	0.5830	0.2460	0.1300	0.1750	Adult
64	64	Male	0.425	0.325	0.095	0.3785	0.1705	0.0800	0.1000	Adult
65	65	Male	0.520	0.400	0.120	0.5800	0.2340	0.1315	0.1850	Adult
66	66	Male	0.475	0.355	0.120	0.4800	0.2340	0.1015	0.1350	Adult
70	70	Infant	0.310	0.235	0.070	0.1510	0.0630	0.0405	0.0450	Adult
72	72	Female	0.400	0.320	0.110	0.3530	0.1405	0.0985	0.1000	Adult
75	75	Female	0.605	0.450	0.195	1.0980	0.4810	0.2895	0.3150	old
76	76	Female	0.600	0.475	0.150	1.0075	0.4425	0.2210	0.2800	Young
77	77	Male	0.595	0.475	0.140	0.9440	0.3625	0.1890	0.3150	old
79	79	Female	0.555	0.425	0.140	0.7880	0.2820	0.1595	0.2850	old
80	80	Female	0.615	0.475	0.170	1.1025	0.4695	0.2355	0.3450	old

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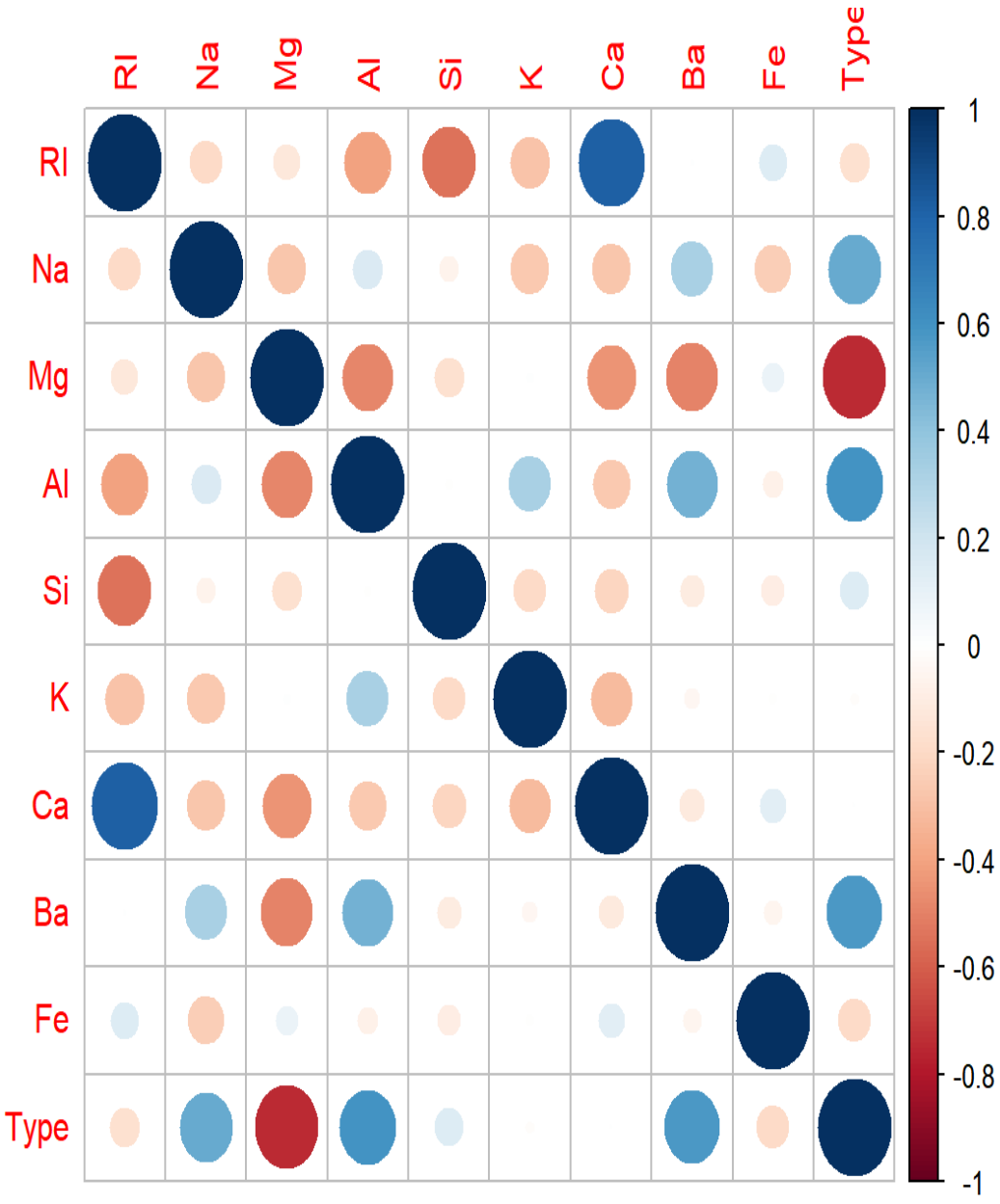

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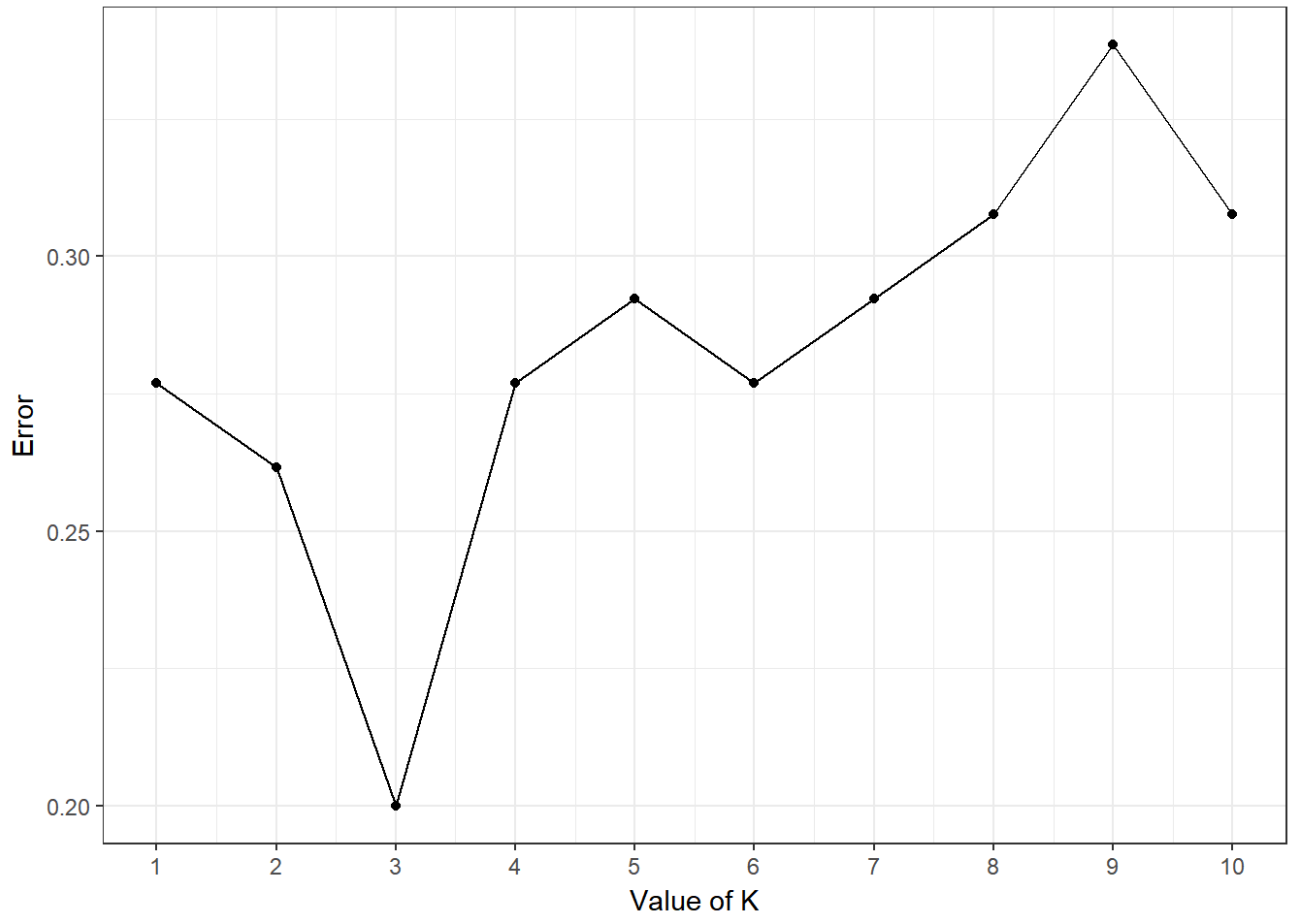

Confusion Matrix:

```
Confusion Matrix and Statistics
##
##          Reference
## Prediction  1  2  3  5  6  7
##          1 19  3  2  0  0  0
##          2  1 18  3  1  0  1
##          3  1  1  0  0  0  0
##          5  0  0  0  3  0  0
##          6  0  1  0  0  3  0
##          7  0  0  0  0  0  8
```

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5. Conclusion And Future Work

5.1 Future Work

The text provided describes the context and approach for predicting the age of abalones based on physical measurements. Here are the key points: Objective: The primary goal is to predict the age of abalones without the need for the time-consuming and invasive process of cutting the shell and counting rings under a microscope. Dataset: The dataset used for this project belongs to Marine Research Laboratories (MRL) in Taroona. Age Determination: Traditionally, abalone age is determined by cutting the shell, staining it, and counting the rings. This is a tedious and time-consuming task. Predictive Features: The project aims to find predictability using eight physical measurements. Some of these measurements can be obtained without harming the abalones, such as sex, length, diameter, height, and whole weight. Limitation: Certain "internal data," including the weight of viscera and shell, cannot be obtained without causing harm to the abalones, which is not acceptable. Cultivating Industry: In the abalone cultivation industry, young abalones are typically kept, while adult and old abalones are harvested. Predicting the age based on "internal data" is not practical, as it would require harming the abalones. Data Split: The dataset is divided into two parts:
"External Data": Includes attributes like sex, length, diameter, height, and whole weight, which can be obtained without harming the abalones. “Internal Data": Includes attributes like the weight of shuck, shell, and viscera, which cannot be obtained without harming the abalones.
Results: The papers findings indicate that the "external data" alone is sufficient to predict the age of abalones with nearly the same success rate as using the entire dataset. Using only the "external data" results in a simplified decision tree. The "internal data" does not provide significantly more information. The project's approach focuses on using non-invasive attributes to predict abalone age, making it more practical and humane for the abalone cultivation industry. This approach simplifies the age prediction process and avoids the need to harm the abalones for data collection.

5.2 Conclusion

The paper's objective is to predict the age of abalones based on various attributes, including sex, length, diameter, height, whole weight, shucked weight, viscera weight, shell weight, and the number of rings. The project employs multiple data mining techniques to analyse the data and evaluate their performance. The overarching goal is to leverage historical data to uncover general patterns and enhance the decision-making process. The project is acknowledged as both interesting and challenging, particularly during the analytical phase. The team has acquired a comprehensive understanding of the knowledge encompassed in the project proposal, reflecting the effort and commitment invested in the project.

6. References

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