**Data Science Post Block Assignment 3: Task A**

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1. **Introduction** 
   1. **Background**

Missing data is a common data quality issue encountered during the data exploration and cleaning phases. If features have hissing values, it is important to determine why these values are missing. Often missing values can creep in during data integration, in these cases, the integration errors can be fixed to resolve the missing value issues [1]. On the other hand, missing values can also be introduced during the data generation or collection phases – these are more difficult to deal with.

There are various ways to deal with missing values. One is to simply remove instances or features that contain them. This is not the best approach as it could lead to the loss of valuable information and may lead to bias during inference [2]. Another method is to convert the missing value into a new feature, but this has shown to lead to serious inference problems [3 according to 2]. Finally, one can impute the missing values. Imputation is generally a good idea if a significant portion of the data contains missing values for a few features. Generally, imputation above 60% of missing values are not recommended [1].

There are different imputation methodologies, of which we will be focusing on the following two:

*Baseline imputation (data driven):* Imputing the variable simply based on the mode(categorical) or mean/median(numerical).

*Model Imputation:* a model is used to perform parameter estimation.

]. Studies have found that the ‘best’ imputation method depends on the type of data in the dataset, the proportion of missing values and even the distribution of the features have an influence on the type of imputation that is considered ‘best’ [2].

* 1. **Objectives**

**Task A:** The objective was to evaluate the effectiveness of a baseline imputation versus that of a Naïve Bayes imputation on the performance of classification models. For this study we also decided to look at the influence of the proportion of missing values on the effectiveness of the imputation method. This will be done by comparing the performance of two classification models who have been trained on the control data and the imputed data and then tested with unchanged data.

1. **Methodology**

In this study, we leveraged R Studio and Python as the primary tools for imputation, modelling, and evaluation. The methodology involved several key steps:

**Data Exploration:** The first phase of the analysis involved exploring the Nursery dataset to gain a comprehensive understanding of their structure, variables, and content. As the main aim of this experiment is to evaluate the effectiveness of two different imputation methods, it was essential that the data be as clean as possible, as not to confuse any possible insights.

**Data Pre-processing:** For this experiment, the pre-processing consisted of splitting the data into a 30:70 test: train split. The testing dataset was then reserved for later use. Three copies of the training data-subset were made and were induced with missing values in varying proportions (10%, 40% and 70%). These together with the training control was then used during the modelling.

**Modelling:** K-Nearest Neighbours Classifier and a Classification Tree was used to evaluate the effectiveness of the data Imputation.

k-Nearest Neighbour: [insert chosen k= 95 and method here]

The K\_ Nearest Neighbours (K-NN) classifier was used as one of the models to train on and validate the performance of the imputation techniques. We used the K-NN classifier in the R studio and Orange to determine how K-NN responds to the various data sets namely, original training sets, original testing, mode data at 10, mode at 40, mode at 70, naïve bayes at 10, naïve bayes at 40, naïve bayes at 70 of the public nursery data set.

The implication of the K-NN is that the model is a simple model that works for both categorical and numerical data sets. This implementation, therefore, required that the data sets be handled in a way the k- NN algorithm could provide outputs into whether the algorithm could effectively learn the data set and predict outcomes through the performance metrics of the accuracy and the F1 score. The K-NN was therefore compared to the control and between the different imputed data of the same Nursery data set. The below steps were the coding methodology utilised in R studio to build the K-NN.

* Importing of the data sets,
* Converting the character data into a factor,
* Converting the factor of the variables within the data sets as numeric,
* Handling missing values if any are identified,
* Training the data and testing data sets,
* Determining the optimal value of k, which is the square root of the total number of observations within the data set,
* Creating predications,
* Developing the K\_NN model from the trained, test and target vectors, and
* Calculating the performance metrices and the confusions matrix.

All the above steps were taken for each of the data sets mentioned above, however noteworthy without ease, particularly for the mode 40 data set, and the naïve bayes data sets at the 40, 70 percentages of imputation.

We then trained the model on the various datasets and tested against the non-imputed base table. For each dataset we recorded the accuracy and F1 score, which was then used to compare model performance across different datasets.

We trained on the base dataset (no missing values induced, or missing values imputed) and report the accuracy and F1 score for this model as the baseline values. These baseline values are then compared to the paired imputed datasets (Same % of missing values imputed using Mode value and Naïve Bayes) against the K-NN Accuracy and F1 score values.

1. **LIMITATION**

Using R Studio for this exercise posed several challenges, primarily due to encountering missing values in the target variable (class) within the original training dataset, as well as in other datasets, including other variables. These missing values were unexpected, considering the initial collation of the dataset was done without any such gaps. Addressing these missing values became necessary as K-NN generated error messages due to their presence, preventing the application of the algorithm.

The occurrence of missing values in R Studio could be attributed to various factors. Firstly, there might have been issues with data file encoding, leading to misinterpretation of certain characters or symbols. Secondly, incorrect interpretation of data types by R, such as numeric values being stored as character strings, could have contributed. Additionally, special characters or non-standard symbols might have caused misinterpretation. Lastly, file corruption or data file structure issues could have played a role in R misreading the data.

An alternative approach involved utilizing orange data mining software to address these challenges. This process entailed importing different datasets, including the testing dataset, utilizing K-NN widgets, employing test score widgets, and utilizing the Confusion Matrix to evaluate the model's predictive performance. The accuracy and F1 score values obtained from Orange K-NN were favoured and incorporated into various tables to visually represent the model's response to the data.

Classification tree: [insert parameter settings here]

**Visualization:** Line plots were constructed to clearly visualise the difference in performance of the two models when trained with data that was imputed in two different ways.

1. **Results and Discussion**

After pre-processing, the optimal number of clusters were to be selected for the K-means clustering.

In the report, it's crucial to summarize the significance of accuracy and F1 score evaluation metrics, particularly in the context of classification tasks, as they offer distinct insights into model performance. Accuracy in machine learning denotes the ratio of correctly classified instances to the total instances, serving as a measure of overall correctness. On the other hand, the F1 score represents the harmonic mean of precision and recall, both essential evaluation metrics. Ranging from 0 to 1, a higher F1 score indicates better model performance.

Upon examining the accuracy levels across different datasets with varying proportions of missing values, noticeable fluctuations are observed. Notably, the accuracy trends vary for different datasets, with K-NN showing high accuracy initially for the naïve Bayes data, followed by a decline and subsequent increase. This indicates a gradual establishment of correctness proportions across the mode datasets at 10, 40, and 70.

Figure 1: K-NN Accuracy performance metric graph comparing the control, mode and naïve bayes imputation techniques.

Figure 2: K-NN F1 performance metric graph comparing the control, mode and naïve bayes imputation techniques.

1. **Conclusion**

In conclusion, the analysis of the

1. **References**
2. AML textbook, page 64
3. Impact of imputation of missing values on classification error for discrete data - article
4. J.L. Shafer, Analysis of Incomplete Multivariate Data, Chapman and Hall, London, 1997.