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Performance analysis of machine learning algorithms for missing value imputation (Article)

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Abstract

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Data mining requires a pre-processing task in which the data are prepared, cleaned, integrated, transformed, reduced and discretized for ensuring the quality. Missing values is a universal problem in many research domains that is commonly encountered in the data cleaning process. Missing values usually occur when a value of stored data absent for a variable of an observation. Missing values problem imposes undesirable effect on analysis results, especially when it leads to biased parameter estimates. Data imputation is a common way to deal with missing values where the missing value's substitutes are discovered through statistical or machine learning techniques. Nevertheless, examining the strengths (and limitations) of these techniques is important to aid understanding its characteristics. In this paper, the performance of three machine learning classifiers (K-Nearest Neighbors (KNN), Decision Tree, and Bayesian Networks) are compared in terms of data imputation accuracy. The results shows that among the three classifiers, Bayesian has the most promising performance. © 2015 The Science and Information (SAI) Organization Limited.

Author keywords

[Bayesian networks](#)
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[Decision tree](#)
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[KNearest neighbors](#)
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