A First Approach on Big Data Missing Values Imputation

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Abstract: Albeit most techniques and algorithms assume that the data is accurate, measurements in our analogic world are far from being perfect. Since our capabilities of storing and processing data are growing everyday, these imperfections will accumulate, generating poorer decisions and hindering any knowledge extraction process carried out over the raw data. One of the most disturbing imperfections is the presence of missing values. Many inductive algorithms assume that the data is complete, thus if they face missing data they will not work properly or the quality of the knowledge extracted will be poorer. At this point there is no sophisticated missing values treatment implemented in any major Big Data framework. In this contribution, we present two novel imputation methods based on clustering that achieve better results than simply removing the faulty examples or filling-in the missing values with the mean that can be easily ported to Spark's MLlib.

1 INTRODUCTION

We are currently surrounded by immense amounts of data. On the Internet data is generated at an exponential rate at an increasingly reduced cost thanks to the great development of storage and network resources (Ramírez-Gallego et al., 2018). The volume of data has exceeded the processing capabilities of the systems. We have entered the era of Big Data (John Walker, 2014), which is defined as of the presence of great volume, speed and variety in the data, three characteristics that were introduced by D. Laney (Laney, 2001) with the requirement of new high-performance processing systems.

In all areas of data science, including Big Data, quality of extra-knowledge depends to a large extent on the quality of the data. It is demonstrated that a low quality of the data leads to a low quality of extracted knowledge. In some cases, preprocessing of data is used to improve data quality, resulting in an increased performance of learning algorithms (García et al., 2015). However, the preprocessing algorithms are also affected by the problem of scalability and they must be redesigned for use with new technologies (Gupta et al., 2016).

This challenging scenario has motivated the term Smart Data (Triguero et al., 2018), which lies around two important characteristics, the *veracity* and the *value* of the data. Smart Data objective is to clean out imperfect data and maintain valuable data (Iafrate, 2014), which can be used for smart decision making.

The presence of missing values (MVs) is one challenging kind of imperfect data, where several values of input attributes are lost due to different reasons. In spite of being easily identifiable, MVs pose a more severe impact in learning models, as most of the techniques assume that the training data provided is complete (García-Laencina et al., 2010). Until recently, practitioners opted to discard the examples containing MVs, but this praxis often leads to severe bias in the inference process (Little and Rubin, 2014). Several techniques have been developed to cope with MVs without discarding examples, but they were originally devised for standard Data Mining frameworks (Luengo et al., 2012). In the Big Data framework, the attention has been recently drawn to cope with this problem, either by taking advantage of the iterative capabilities of Spark by using a repeated approximated clustering algorithm to impute MVs (Kaliamoorthy and Bhanu, 2018) or the usage of artificial distributed neural networks to compute the numerical MVS (Petrozziello et al., 2018). This work is on the line of the latter, offering a scalable solution that can be exploited by posterior learning algorithms.

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The main goal of this work is to propose two Big Data preprocessing techniques to impute MVs. We will use the K-Means and Fuzzy-K-Means algorithms as imputation techniques where we will generate the MVs through the information of the clusters (Li et al., 2004). These two approaches will be implemented under Spark (Zaharia et al., 2016), redesigning the original algorithms to take full advantage of the MapReduce paradigm. The proposed techniques will be validated using different well-known data sets for Big Data classification benchmarking. In particular, we will simulate different amount of MVs to check whether our proposal behave correctly in low to high missing data scenarios and we will evaluate the effect of the number of centroids selected in the performance and running times.

The rest of this contribution is organized as follows. Section 2 will introduce the background on MV imputation. Section 3 describe the two imputation techniques proposed. Section 4 contains the experimental analysis carried out with the proposals and the compared techniques. Finally, Section 5 presents the conclusions of our work.

2 MISSING VALUES TREATMENT

In the last few decades, a great deal of progress has been made in our capacities to generate and store data, basically due to the great power of the processing of the machines in addition to its low cost of storage. However, within these huge volumes of data, there is a large amount of hidden information, of great strategic importance. The discovery of this hidden information is possible thanks to Big Data techniques, which applies machine learning algorithms to find patterns and relationships within the data, allowing the creation of models and abstract representations of reality.

To ensure that extracted models are accurate, the quality of the source data must be as high as possible. Sadly, real-world data sources are often subject to imperfections that will diminish such quality. It is in this scenario where data preprocessing techniques are demanded, by cleaning and transforming the data to increment its quality.

Among the main problems of real-world data, MVs are one of the most challenging problems, as the majority of Big Data techniques assume that the data is complete. In such a way, the presence of MVs will disallow any practitioner to utilize a large set of techniques. Hence, the treatment of MVs is one of the main paradigms within imperfect data treatment.

Before deciding applying any preprocessing technique, we must acknowledge the type of missingness we are facing. The statistical dependencies among the corrupted and clean data will dictate how the imperfect data can be handled. Originally, Little and Rubin (Little and Rubin, 2014) described the three main mechanisms of MVs introduction. When the MV distribution is independent of any other variable, we face Missing Completely at Random (MCAR) mechanism. A more general case is when the MV appearance is influenced by other observed variables, constituting the Missing at Random (MAR) case. These two scenarios enable the practitioner to utilise imputators to deal with MVs. Inspired by this classification, Frénay and Verleysen (Frénay and Verleysen, 2014) extended this classification to noise data, analogously defining Noisy Completely at Random and Noisy at Random. Thus, noise filters can only be safely applied with these two scenarios.

Alternatively, the value of the attribute itself can influence the probability of having a MV or a noisy value. These cases were named as Missing Not at Random (MNAR) and Noisy Not at Random for MVs and noisy data, respectively. Blindly applying imputators in this case will result in a data bias. In these scenarios, we need to model the probability distribution of the missingness mechanism by using expert knowledge and introduce it in statistical techniques as Multiple Imputation (Royston et al., 2004). To avoid improperly application of correcting techniques, some test have been developed to evaluate the underlying mechanisms (Little, 1988) but still careful data exploration must be carried out first.

Once we acknowledge the kind of MVs we are facing, there are different ways to approach the problem of MVs. For the sake of simplicity, we will focus on the MCAR and MAR cases by using imputation techniques, as MNAR will imply a particular solution and modeling for each problem. When facing MAR or MCAR scenarios, the simplest strategy is to discard those instances that contain MVs. However, these instances may contain relevant information or the number of affected instances may also be extremely high, and therefore, the elimination of these samples may not be practical or even bias the data.

Instead of eliminating the corrupted instances, the imputation of MVs is a popular option (Little and Rubin, 2014). The simplest and most popular estimate used to impute is the average value of the whole dataset, or the mode in case of categorical variables. Mean imputation would constitute a perfect candidate to be applied in Big Data environments as the mean of each variable remains unaltered and can be performed in $O(n)$. However, this procedure presents drawbacks that discourage its usage: the relationship among the

variables is not preserved and that is the property that learning algorithms want to exploit. Additionally, the standard error of any procedure applied to the data is severely underestimated (Little and Rubin, 2014) leading to incorrect conclusions.

Further developments in imputation are to solve the limitations of the two previous strategies. Statistical techniques such as Expectation-Maximization (Schneider, 2001) or Local Least Squares Imputation (Kim et al., 2004) were applied in bioinformatics or climatic fields. Note that imputing MVs can be described as a regression or classification problem, depending on the nature of the missing attribute. Shortly after, computer scientists propose the usage of machine learning algorithms to impute MVs (Luengo et al., 2012).

Nowadays, data imputation in Big Data frameworks is being explored more and more. Qu et al. (Qu et al., 2016) proposed the usage of a distributed Apriori to estimate nominal attributes over a single dataset. Petrozziello et al. (Petrozziello et al., 2018) on the other hand tackled the MV problem by using distributed artificial neural networks over a sales travel industry problem, showing a good performance with numerical attributes. If we take into account clustering algorithms for imputation, Kaliamoorthy et al. (Kaliamoorthy and Bhanu, 2018) created a multiple imputation algorithm with an approximate version of fuzzy k-means, but without any prior knowledge about the data distribution.

In this work we deepen in the last approach, by proposing two novel techniques to deal with MVs in Big Data, as shown in the next section. Instead of comparing the performance of the proposals in terms of imputation accuracy, we want to explore the impact of a correct imputation in the latter learning algorithms applied.

3 BIG DATA MISSING VALUES IMPUTATION

This section presents the two proposed techniques for Big Data MVs imputation. Section 3.1 is devoted to describe the K-means imputation. Section 3.2 presents the Fuzzy K-means imputation.

3.1 Big Data K-means Imputation

The implementation of the two proposed MVs imputation methods is enclosed under MLib. MLib is the machine learning library offered by Spark. Among its methods, K-means clustering is available at https://github.com/apache/spark/blob/master/mllib/src/main/scala/org/apache/spark/mllib/clustering/KMeans.scala. Such implementation will be used as a basis to develop the Big Data K-Means Imputation (BD-KMI).

First of all, MLlib K-means algorithm is intended for data complete, i.e. for data that do not have missing values. Instead of using the Dense Vector to represent the examples, we modified the implementation to work with the Sparse Vector class. In such a way, we can detect whether an example contains a MV by comparing the number of stored values with the number of indices actually used.

The distance calculation had to be modified as well, since the original implementation only accounted for complete instances. To take into account the presence of MVs, the distance calculation is based on normalized instances (done in a previous step). Thanks to such normalization, when a MV is found, the difference between the attribute's values is set to 1.0, the largest possible.

Once these modifications have been introduced to deal with MVs, BD-KMI is divided into two main steps: (i) the clustering stage and (ii) the imputation step.

The *clustering stage* is composed of the following steps, executed repeatedly until convergence is found, as shown in Figure 1:

1. **Initialization of the Centroids:** The first process that takes place is the establishment of the initial centroids. In this process, the following are chosen from a random selection of the data, in addition we should take special care not to choose elements that contain values lost.
2. **Map Phase:** The next process that takes place is the mapping phase, where the mapPartition function is used to split the data in different partitions. In each partition and for each data of the same one, we calculate the nearest centroid and then we carry out two operations. On the one hand we increase in one the counter that indicates the number of elements that belong to a centroid. On the other hand we add that data to the cumulative sum of the cluster data represented by the centroid. For each partition, we will obtain an array of Kx2(K represents the number of centroids) and where each represents a cluster with the number of elements that belong to that cluster and the sum of the vectors of all those elements.
3. **Reduce Phase:** In the next stage of reduction we group the results of each one of the partitions, in such a way that when nalizar the stage reduces we have the sums of the different counters and the sum of vectors but for the entire dataset.

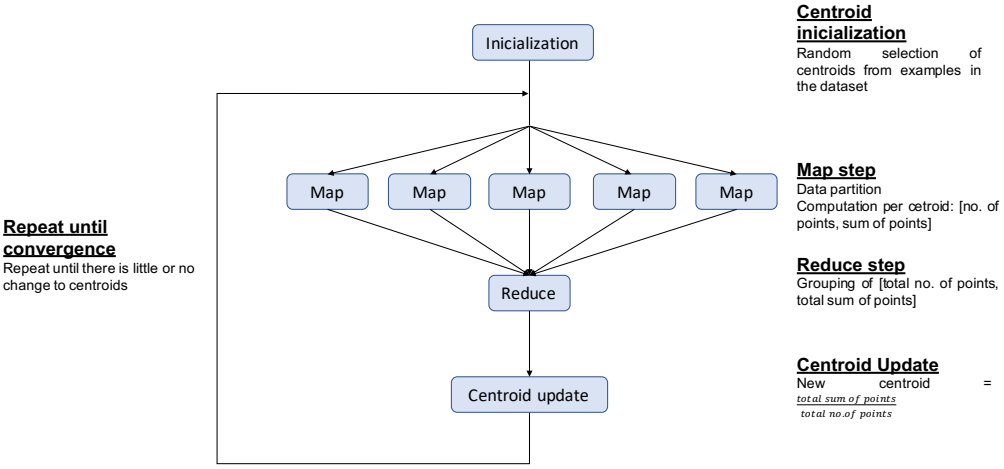


Figure 1: Big Data K-means Imputation outline.

4. **Centroid Update:** Once obtained the information on the centroids, we proceed to update it. For it we will use the two data on the centroids obtained in the previous phases. To obtain the new centroid we divide the vector resulting from the sum of the data that belong to the cluster by the number of elements of the same, in this way the centroid will be readjusted and placed at the midpoint according to the elements that belong to the cluster it represents.

Steps 2 to 4 are repeated until the centroids converge. The convergence is evaluated by comparing the "movement" differences of the centroids between iterations with a given threshold.

Once the centroids have been obtained, we proceed with the *imputation stage* of the data that have lost values. We go through all the examples, detecting those with MVs, determining which cluster it belongs to, and therefore the centroid that represents it.

Once the centroid that represents the example with lost values is obtained, we replace those missing values with the corresponding attributes belonging to the centroid.

3.2 Big Data Fuzzy K-means Imputation

Big Data Fuzzy K-means Imputation (BD-FKMI) is based on the fuzzy version of K-means, which implies that the examples will belong to all centroids but with a given membership degree. If we consider the differences among KMI and FKMI, we must point out two of them before describing our proposal:

- Updating the centroids must consider all examples, not only those that are the closest to it. As a result, from each point we get, instead of the nearest centroid index, a vector of degrees of belonging, where each element of the vector corresponds to the membership degree that has that point with each centroid.
- The data structure we have to calculate for each centroid is no longer [no of points, cumulative sum of points], but, following the formula of the diffuse grouping algorithm, we calculate for each centroid [sum of degrees, cumulative sum of points $\times$ corresponding degree to the centroid].

The algorithm follows the same structure and the same series of processes than BD-KMI, but we need to take into account the aforementioned differences into the *Map step*. We describe the main algorithmic steps next, by following the schemata presented in Figure 2. The membership calculation is the same as the carried out in (Li et al., 2004) and for the sake of brevity we will not reproduce entirely here.

1. **Initialization of the Centroids:** Just like KMI, the initial centroids are randomly selected.
2. **Map Phase:** For each example in each partition we compute a vector that represents the membership degree to each of the centroids. In this case the result of the execution of each partition will result in a $K \times 2$ matrix where the information of each centroid is, (i) the sum of all membership degrees for each example and; (ii) the sum of each of these data multiplied by its corresponding membership degree.
3. **Reduce Phase:** We group the results of each of the partitions to obtain information on the total of the data.
4. **Centroid Update:** We divide the sum of the data by the sum of the degrees respect to each centroid.

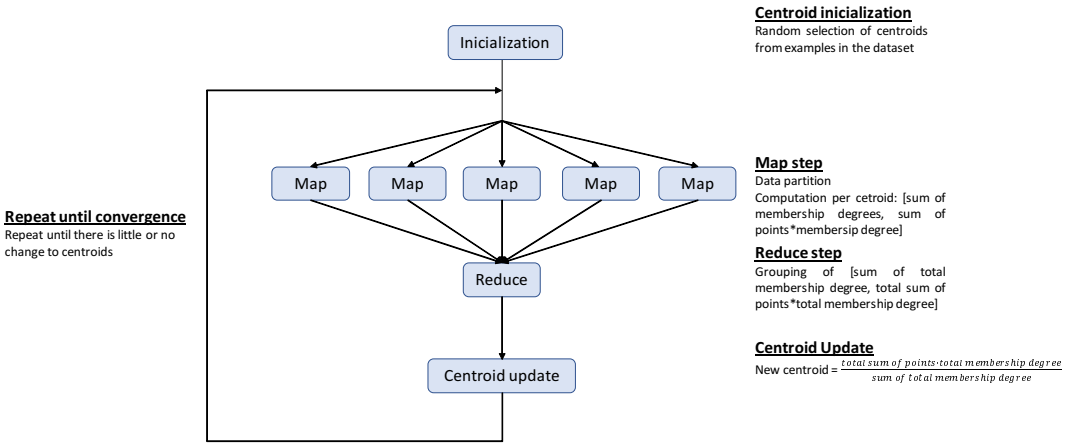


Figure 2: Big Data Fuzzy K-means Impute outline

Steps 2 to 4 are repeated until the convergence of the centroids is attained, in a similar fashion to BD-KMI.

4 EXPERIMENTAL ANALYSIS

In this section we experimentally validate the proposed algorithms with some well-known Big Data benchmark datasets. Section 4.1 describes the experimental framework used in our experiments. Section 4.2 is devoted to the analysis of the experiments' results. Finally, Section 4.3 will present the computation times for the compared approaches.

4.1 Experimental Framework

In order to compare the different techniques, we have considered three well-known Big Datasets, which follows:

- **Susy:** It has about 4 million instances with 19 attributes. The data have been obtained through Monte Carlo simulations. The first 8 attributes are kinematic properties measured by the particle detectors on the accelerator while the last ten characters are functions of the first 8 attributes.
- **Higgs10:** It has approximately 880 thousand instances of 29 attributes each. As the previous dataset was obtained through the Monte Carlo method in the experimentation on subatomic particles.
- **ECBDL14:** The latest dataset is the largest one. In the beginning it was devised for the prediction of protein structure, and it was originally generated to train a predictor related to contact map prediction in the CASP9 competition for ECBDL'14 conference. It has 2 million instances and 631 attributes.

Table 1: Parameters for the classifiers.

Classifier	Parameters
DT	depth: 20, maxBins: 20
RF	numTrees: 20, depth: 20, maxBins: 20
ANN	epochs: 50, layers: 2 neuronsLayer1: 18, neuronsLayer2: 2

Since the aforementioned datasets do not contain MVs, we will artificially induce missing data in them following a MCAR schema. The only restriction applied is to induce only one MV per example, which would be more representative of MCAR (since having more MVs in some instances would be related to a MAR schema). The amount of MVs induce will be 5, 10 and 30%, ranging from a low to highly MV scenario.

As we have previously mentioned, there is no other non-naïve imputation technique in Big Data. Thus, we are limited to compare our two proposed techniques either with:

- Deleting or *ignoring* the examples with MVs, named as *IC*.
- Imputation by the mean value of each input attribute, named as *MC*.

These two techniques are easily implemented in Spark by using filter to detect the missing values and the native functions to compute the cumulative summation of values in order to compute the mean value.

We want to evaluate how the imputation of the compared techniques affects the performance of the classifiers that would be used afterwards. To properly evaluate such impact, we have selected some representative classifiers from MLib, which follows: de-

Table 2: Accuracy results for Susy dataset.

	5% of missing values			10% of missing values			30% of missing values		
	DT(Acc)	RF(Acc)	ANN(Acc)	DT(Acc)	RF(Acc)	ANN(Acc)	DT(Acc)	RF(Acc)	ANN(Acc)
BD-KMI(k=5)	0.782447	0.799291	**0.783058**	**0.784201**	0.799192	**0.782340**	**0.787823**	0.798408	0.780787
BD-KMI(k=15)	**0.782540**	0.799369	0.781930	0.784022	0.799221	0.781861	0.787458	0.798824	0.781265
BD-KMI(k=30)	0.781936	0.799334	0.781498	0.783486	0.799293	0.782304	0.786973	0.798929	0.781072
BD-FKMI(k=5)	0.781641	0.799301	0.782231	0.782242	0.799202	0.780907	0.782855	0.798951	**0.782452**
BD-FKMI(k=15)	0.781594	0.799348	0.781792	0.781486	0.799240	0.780951	0.782891	0.799054	0.782373
BD-FKMI(k=30)	0.781641	0.799245	0.781943	0.782154	0.799250	0.780796	0.783080	0.798977	0.782401
MC	0.781722	**0.799384**	0.782297	0.782090	**0.799349**	0.781459	0.782357	**0.799070**	0.782087
IC	0.780501	0.798985	0.781928	0.780040	0.799344	0.782029	0.777843	0.799021	0.782057

Table 3: Accuracy results for Higgs dataset.

	5% of missing values			10% of missing values			30% of missing values		
	DT(Acc)	RF(Acc)	ANN(Acc)	DT(Acc)	RF(Acc)	ANN(Acc)	DT(Acc)	RF(Acc)	ANN(Acc)
BD-KMI(k=5)	0.683908	0.738168	**0.628632**	0.683232	0.737928	0.628159	0.682132	0.736913	0.628458
BD-KMI(k=15)	0.684011	**0.738520**	0.628272	0.683273	0.738078	0.627418	0.682167	0.736360	0.628511
BD-KMI(k=30)	**0.684859**	0.738268	0.627457	0.683835	0.737781	**0.628733**	0.682639	0.735936	0.628422
BD-FKMI(k=5)	0.684150	0.738195	0.627073	**0.684333**	0.737652	0.628078	0.682935	0.736784	0.628576
BD-FKMI(k=15)	0.684551	0.737827	0.627108	0.684171	0.737634	0.628078	0.683145	**0.737112**	0.628576
BD-FKMI(k=30)	0.683248	0.738243	0.627617	0.683639	**0.738264**	0.628078	**0.683178**	0.736725	0.628575
MC	0.684455	0.738275	0.627280	0.683708	0.737812	0.627210	0.681988	0.736915	**0.628594**
IC	0.682120	0.737390	0.627537	0.682118	0.736260	0.628446	0.675251	0.732435	0.628260

cision tree (DT), Random Forest (RF), and an artificial neural network (ANN). The parameters used for these classifiers have been experimentally adjusted for the original datasets to obtain a good performance by means of grid search, and then later applied to the imputed version of the same datasets. The obtained parameters can be found in Table 1. Both BD-KMI and BD-FKMI only require to specify the number of centroids k. For both imputation techniques we will consider $k = 5, 15, 30\%$ We have used a 5-fcv validation to validate our proposals.

For all experiments we have used a cluster composed of 20 computing nodes and one master node. The computing nodes hold the following characteristics: 2 processors x Intel Xeon(R) CPU E5-2620, 6 cores per processor, 2.00 GHz, 2 TB HDD, 64 GB RAM. Regarding software, we have used the following configuration: Hadoop 2.6.0-cdh5.4.3 from Cloudera's open source Apache Hadoop distribution, Apache Spark and MLlib 1.6.0, 460 cores (23 cores/node), 960 RAM GB (48 GB/node).

4.2 Accuracy Analysis with the Imputation Methods

In this section we will analyze the results obtained by the classification methods once the imputation methods have been applied for each dataset individually.

Table 2 presents the results for the Susy dataset. From the results presented, the best imputation technique is BD-KMI, where in most cases it performs best with few clusters. On the other hand, we must stress that mean imputation (MC) is the best technique for RF. Due to the fact that MC maintains the variance of the attribute, which RF can exploit better thanks to its sampling. Thus, a multi-classifier with the capability of generating diverse base classifiers could be more robust to naïve methos as MC. Nevertheless, BD-KMI is the second best to RF, being the most balanced option for Susy.

In Table 3 we show the results for Higgs dataset. In this case, there is a clear domain of imputation based in clustering. In general, the FKMI imputter offers better results for datasets with high percentages of missing values. However, for lower percentages of missing values, BD-KMI obtains the best precision scores. For this dataset, MC does not achieve the high performance that was observed for RF in Susy.

Finally, Table 4 depicts the accuracy results in the case of ECDBL'14 dataset. Observing the results, BD-FKMI offers better results. As for the number of centroids, it appears that BD-KMI gives better performance with higher k, while in the case of BD-FKMI this value varies to a greater extent. Comparing our proposal with MC, the latter only out-stands (with a narrow margin) when the number of MVs is medium to high and only for DT. Thus, the option of using imputation-based techniques is the safest option for ECDBL'14 dataset.

As a general analysis, we can consider that the proposed imputation methods outperform both MC and IC. We must stress that deleting examples with

Table 4: Accuracy results for ECDBL'14 dataset.

	5% of missing values			10% of missing values			30% of missing values		
	DT(Acc)	RF(Acc)	ANN(Acc)	DT(Acc)	RF(Acc)	ANN(Acc)	DT(Acc)	RF(Acc)	ANN(Acc)
BD-KMI(k=5)	0.980086	0.980233	0.980234	0.980083	0.980230	0.980233	0.980105	0.980234	0.980234
BD-KMI(k=15)	0.980067	0.980231	0.980232	0.980090	0.980235	0.980234	0.980100	0.980234	0.980234
BD-KMI(k=30)	0.980079	**0.980234**	0.980234	0.980078	**0.980236**	0.980235	0.980101	0.980233	0.980234
BD-FKMI(k=5)	**0.980105**	0.980233	0.980234	0.980101	0.980233	**0.980235**	0.980106	0.980236	0.980232
BD-FKMI(k=15)	0.980095	0.980232	**0.980236**	0.980090	0.980235	0.980235	0.980099	0.980227	0.980234
BD-FKMI(k=30)	0.980096	0.980231	0.980232	0.980109	0.980231	0.980233	0.980103	**0.980237**	**0.980237**
MC	0.980104	0.980233	0.980235	**0.980126**	0.980226	0.980235	**0.980153**	0.980229	0.980233
IC	0.980079	0.980231	0.980234	0.980037	0.980232	0.980234	0.980065	0.980234	0.980234

MVs (IC) is never the best option, and thus we are being able to recover part of the information lost in all scenarios, from low to high amount of MVs.

As for which version of the clustering based imputation we should choose, the choice depends on the dataset. For instance, Susy dataset favors BD-KMI, while for the two other datasets, we get better results when using BD-FKMI. The number of centroids chosen depends on the dataset as well. However, this is a known feature of the original K-means clustering technique and therefore, such behavior is inherited by the imputation methods.

4.3 Running Times Analysis

In this section we present the running times for the imputation methods and the impact that the number of chosen centroids have in the performance. Figures 3a to 3c depict the running times in minutes for each approach compared in the three benchmark datasets. As we may appreciate, the fuzzy version BD-FKMI is slower than its crisp version BD-KMI for the same value of k. This overhead is a logical consequence of the membership calculation for all the centroids that BD-FMKI carries out and was also present in the non Big Data version of both imputation methods.

We may also appreciate that IC has a running time of almost zero in all cases. Since IC was implemented with a native filter of Spark, its efficiency is very high. However, we have shown in the previous section that IC is never the best option to deal with MVs.

MC is also very efficient and not depends on the amount of MVs. Since the implementation of MC implies the cumulative sum of all observed values in the Map phase and the later division in the Reduce step, the number of MVs will affect little to the sum carried out. Again, MC is a very simple method that will run fast, but we have also shown that it is rarely the best option.

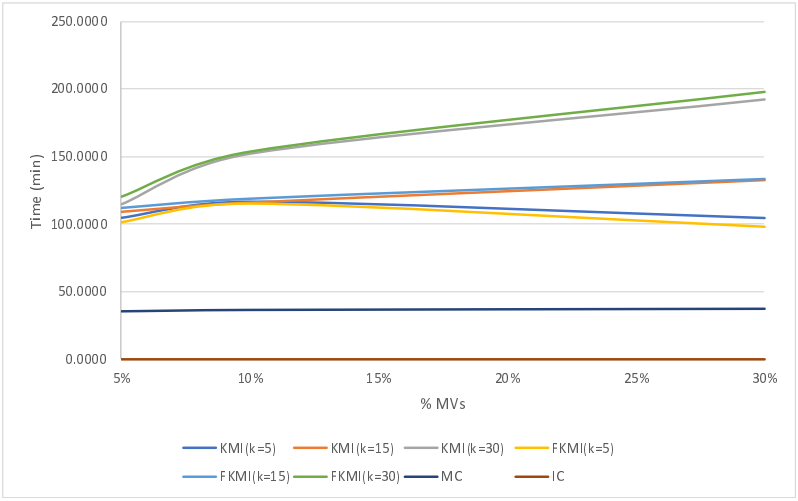
Both BD-KMI and BD-FKMI increase their running times as the number of MVs increase as the number of imputations carried out will increase with the number of MVs. Increasing the number of centroids k has a negative impact in the performance. However, as occurs for Higgs dataset, the number of k can be too high, causing a premature stagnation in the clustering process and thus ending the process before reaching the max number of iterations.

5 CONCLUSIONS

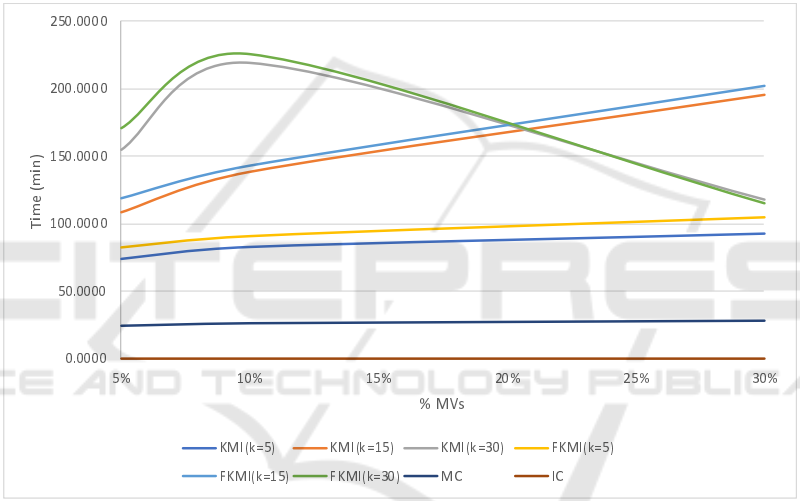
Two imputation techniques for MVs have been implemented in Big Data that, although simple, constitute a good starting point for futures developments of the same type. Although Spark offers the machine learning library (MLlib), it is in continuous growth and lacks many algorithms important for the treatment of MVs. The two implemented techniques offer robust and efficient results for Big Data datasets, offering reasonable execution times. Both imputation methods surpass in most cases other two classic techniques of treatment of MVs, such as mean imputation and elimination of the instances with lost values. It is it is important to highlight the fact that both BD-KMI and BD-FKMI outperform the method of eliminating instances with MVs, since this will prevent a possible loss of valuable information.

Regarding to the performance difference between the two proposed imputation methods, experiments show that BD-FKMI provides better results for high percentages of MVs in the dataset, while the BD-KMI performs better for dataset with lower amounts of MVs. One of the aspects that we wanted to deeper analyze is the influence of the number of centroids. The results show that the influence of this parameter is very dependent of the dataset. The increase in the number of centroids in our experiments will not always improve accuracy results. On the other hand, this increase has impact on computational time, which is why we have not reached higher k values in our experiments.

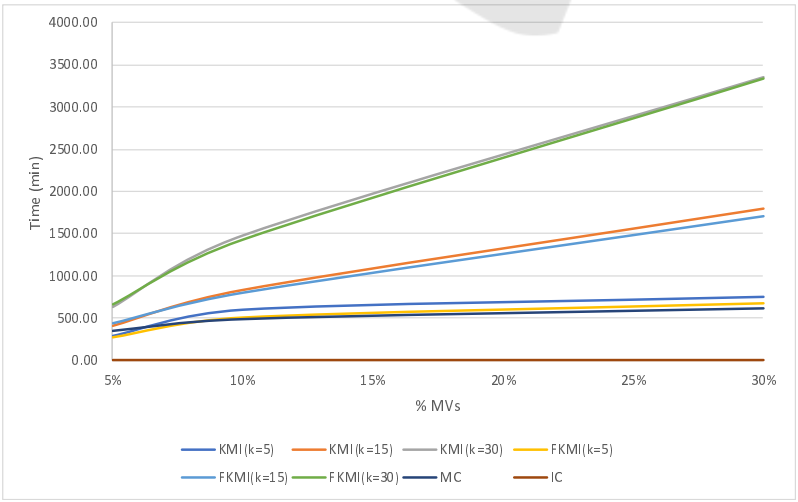
As a future work, we intend to implement a smarter way to select the initial centroids, which has a great impact in the solution found by any K-means variant. An additional improvement that we will con-



(a) Running times in minutes for Susy dataset



(b) Running times in minutes for Higgs dataset



(c) Running times in minutes for ECDBL'14 dataset.

Figure 3.

sider will be changing how the MVs are imputed. Instead of taking the reference attribute's value from the centroid, we will consider the use of a k-nearest neighbor imputation among the closest examples in the cluster, which may yield a closer imputed value instead of always taking centroid's attribute value.

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