# POP: A Parallel Optimized Preparation of Data for Data Mining

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Abstract: In light of the fact that data preparation has a substantial impact on data mining results, we provide an original framework for automatically preparing the data of any given database. Our research focuses, for each attribute of the database, on two points: (*i*) Specifying an optimized outlier detection method, and (*ii*), Identifying the most appropriate discretization method. Concerning the former, we illustrate that the detection of an outlier depends on if data distribution is normal or not. When attempting to discern the best discretization method, what is important is the shape followed by the density function of its distribution law. For this reason, we propose an automatic choice for finding the optimized discretization method based on a multi-criteria (Entropy, Variance, Stability) evaluation. Processings are performed in parallel using multicore capabilities. Conducted experiments validate our approach, showing that it is not always the very same discretization method that is the best.

## 1 INTRODUCTION AND MOTIVATION

Parallel architectures have become a standard when we think about modern architectures. Historically, processors were designed to provide parallel instructions, then operating systems were built in order to accept them, in particular the task (including the thread) manager. As a result of these advances, applications can be distributed on several cores. Consequently, multicore applications run faster given that they require less processor time to be executed. However, they may need more memory since each thread requires its own amount of memory.

On the other hand, many methods exist to prepare data (Pyle, 1999), even if data preparation is few developed in the literature: The accent is more often put on the single mining step. It is obvious that raw input data must be prepared in any KDD (Knowledge Discovery in Databases) system for the mining step. This is for two main reasons: (*i*) If each value of each column is considered as a single item, there will be a combinatorial explosion of the search space, and thus very large response times and/or few values returned, and (*ii*) We cannot expect this task to be performed by an expert because manual cleaning is time consuming and subject to many errors. The data preparation step is generally divided into:

*a*) Preprocessing: Which consists in reducing the data structure by eliminating columns and rows of low significance (Stepankova et al., 2003). Outliers are removed at this step. In addition, we can perform an elimination of concentrated data by removing columns having a small standard deviation or containing too few distinct values;

*b*) Transformation: Discrete values deal with intervals of values (also called bins, clusters, classes, *etc.*), which are more concise for representing knowledge, in a way that they are easier to use and more comprehensive than continuous values. Many discretization algorithms (*see* Section 4.1) have been proposed over the years to achieve this goal.

But data preparation often focuses on a single parameter (discretization method, outlier detection, null values management, *etc.*). Associated specific proposals only highlight on their advantages comparing themselves to others. There is no global nor automatic approach taking advantage of all of them.

However, the better data are prepared, the better results are. Previously in (Ernst and Casali, 2011), we proposed a simple but efficient approach for preparing input data in order to transform them into a set of intervals to which we apply specific mining algorithms to detect: Correlation Rules (Casali and Ernst,

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2013), and Association Rules (Agrawal et al., 1996). The reasons for which we have decided to reconsider our previous work are: (*i*) To improve the detection of outliers with regard to the data distribution (normal or not), (*ii*) To propose an automatic choice of the best discretization method, and (*iii*) To parallelize these jobs.

Globally, the objective of the presented work is to determine automatically the values of most of the data preparation variables, with a focus set on outlier and discretization management. In terms of implementation, corresponding "tasks" are performed for each attribute in parallel. And finally, we carry out experiments.

The paper is organized as follows: Section 2 presents "current" aspects of multicore programming we use in our work. Section 3 and Section 4 are respectively dedicated to outlier detection and to discretization methods. Each Section is composed of two parts: (*i*) a related work, and (*ii*) our approach for improving it. In Section 5, we show the results of the first experimentations. The last Section summarizes our contribution and outlines some research perspectives.

## 2 NEW FEATURES IN MULTICORE ENCODING

Multicore processing is not a new concept, however only in the mid 2000s has the technology become mainstream with Intel and AMD. Moreover, since then, novel software environments that are able to take advantage simultaneously of the different existing processors have been designed (Cilk++, Open MP, TBB, *etc.*). They are based on the fact that looping functions are the key area where splitting parts of a loop across all available hardware resources increase application performance.

We focus hereafter on the relevant versions of the Microsoft .NET framework for C++ proposed since 2010. These enhance support for parallel programming by several utilities, among which the Task Parallel Library. This component entirely hides the multithreading activity on the cores: The job of spawning and terminating threads, as well as scaling the number of threads according to the number of available cores, is done by the library itself.

The Parallel Patterns Library (PPL) is the corresponding available tool in the Visual C++ environment. The PPL operates on small units of work called Tasks. Each of them is defined by a λ calculus expression (see below). The PPL defines three kinds of facilities for parallel processing, where only templates for algorithms for parallel operations are of interest for this presentation.

Among the algorithms defined as templates for initiating parallel execution on multiple cores, we focus on the *parallel_invoke* algorithm used in the presented work (see Sections 3.2 and 4). It executes a set of two or more independent Tasks in parallel. Another novelty introduced by the PPL is the use of λ expressions, now included in the C++11 language norm: These remove all need for scaffolding code, allowing a "function" to be defined in-line in another statement, as in the example provided by Listing 1. The λ element in the square brackets is called the capture specification: It relays to the compiler that a λ function is being created and that each local variable is being captured by reference. The final part is the function body.

```
// Returns the result of adding a value to itself
template <typename T> T twice(const T& t) {
        return t + t;
}
int n = 54; double d = 5.6; string s = "Hello";

// Call the function on each value concurrently
parallel_invoke(
        [&n] { n = twice(n); },
        [&d] { d = twice(d); },
        [&s] { s = twice(s); }
);
```

Listing 1: Parallel execution of 3 simple tasks.

Listing 1 also shows the limits of parallelism. It is widely agreed that applications that may benefit from using more than one processor necessitate: (*i*) Operations that require a substantial amount of processor time, measured in seconds rather than milliseconds, and (*ii*), Operations that can be divided into significant units of calculation which can be executed independently of one another. So the chosen example does not fit parallelization, but is used to illustrate the new features introduced by multicore programming techniques.

More details about parallel algorithms and the λ calculus can be found in (Casali and Ernst, 2013).

## 3 DETECTING OUTLIERS

An outlier is an atypical or erroneous value corresponding to a false measurement, an unwritten input, *etc.* Outlier detection is an uncontrolled problem because values that are not extreme deviate too greatly in comparison with the other data. In other words, they are associated with a significant deviation from the other observations (Aggarwal and Yu, 2001). In this section, we present some outlier detection methods associated to our approach using only uni-variate data as input.

The following notations are used to describe outliers: $X$ is a numeric attribute of a database relation, and is increasingly ordered. $x$ is an arbitrary value, $X_i$ is the $i^{th}$ value, $N$ the size of $X$, $\sigma$ its standard deviation, $\mu$ its mean, and $s$ a central tendency parameter (variance, inter-quartile range, ...). $X_1$ and $X_N$ are respectively the minimum and the maximum values of $X$. $p$ is a probability, and $k$ a parameter specified by the user, or computed by the system.

## 3.1 Related Work

We discuss hereafter four of the main uni-variate outlier detection methods.

**Elimination After Standardizing the Distribution:** This is the most conventional cleaning method (Aggarwal and Yu, 2001). It consists in taking into account $\sigma$ and $\mu$ to determine the limits beyond which aberrant values are eliminated. For an arbitrary distribution, the inequality of Bienaymé-Tchebyshev indicates that the probability that the absolute deviation between a variable and its average is greater than $p$ is less than or equal to $\frac{1}{p^2}$:

$$P(\left|\frac{x-\mu}{\sigma}\right| \geq p) \leq \frac{1}{p^2} \quad (1)$$

The idea is that we can set a threshold probability as a function of $\sigma$ and $\mu$ above which we accept values as non-outliers. For example, with $p = 4.47$, the risk of considering that $x$, satisfying $\left|\frac{x-\mu}{\sigma}\right| \geq p$, is an outlier is bounded by 0.05.

**Algebraic Method:** This method, presented in (Grun-Rehomme et al., 2010), uses the relative distance of a point to the "center" of the distribution, defined by: $d_i = \frac{|X_i-\mu|}{\sigma}$. Outliers are detected outside of the interval $[\mu - k \times Q_1, \mu + k \times Q_3]$, where $k$ is generally fixed to 1.5, 2 or 3. $Q_1$ and $Q_3$ are the first and the third quartiles respectively.

**Box Plot:** This method, attributed to Tukey (Tukey, 1976), is based on the difference between quartiles $Q_1$ and $Q_3$. It distinguishes two categories of extreme values determined outside the lower bound ($LB$) and the upper bound ($UB$):

$$\begin{cases} LB = Q_1 - k \times (Q_3 - Q_1) \\ UB = Q_3 + k \times (Q_3 - Q_1) \end{cases} \quad (2)$$

**Grubbs' Test:** Grubbs' method, presented in (Grubbs, 1969), is a statistical test for lower or higher abnormal data. It uses the difference between the average and the extreme values of the sample. The test is based on the assumption that the data have a normal distribution. The statistic used is: $T = max(\frac{X_N-\mu}{\sigma}, \frac{\mu-X_1}{\sigma})$. The tested value ($X_1$ or $X_N$) is not an outlier is rejected at significance level $\alpha$ if:

$$T > \frac{N-1}{\sqrt{n}}\sqrt{\frac{\beta}{n-2\beta}} \quad (3)$$

where $\beta = t_{\alpha/(2n),n-2}$ is the quartile of order $\alpha/(2n)$ of the Student distribution with $n-2$ degrees of freedom.

## 3.2 An Original Method for Outlier Detection

Most of the existing outlier detection methods assume that the distribution is normal. However, we found that in reality, many samples have asymmetric and multimodal distributions, and the use of these methods can have a significant influence at the data mining step. In such a case, we must process each "distribution" using the appropriate method. The considered approach consists in eliminating outliers in each column based on the normality of data, in order to minimize the risk of eliminating normal values.

Many tests have been proposed in the literature to evaluate the normality of a distribution: Kolmogorov-Smirnov (Lilliefors, 1967), Shapiro-Wilks, Anderson-Darling, Jarque-Bera (Jarque and Bera, 1980), *etc.*. If the former gives the best results whatever the distribution of the analyzed data may be, it is nevertheless much more time consuming to compute then the others. This is why we chosed the Jarque-Bera test (noted JB hereafter), much more simpler to implement as the others, as shown below:

$$JB = \frac{n}{6}(\gamma_3{}^2 + \frac{\gamma_2^2}{4}) \quad (4)$$

This test follows a law of $\chi^2$ with two degrees of freedom, and uses the *Skewness* $\gamma 3$ and the *Kurtosis* $\gamma_2$ statistics, defined as follows:

$$\gamma_3 = E[(\frac{x-\mu}{\sigma})^3] \quad (5)$$

$$\gamma_2 = E[(\frac{x-\mu}{\sigma})^4] - 3 \quad (6)$$

If the JB test is not significant (the variable is normally distributed), then the Grubbs' test is used at a significance level of systematically 5%, otherwise the *Box plot* method is used with parameter $k$ automatically set to 3.

Figure 1 summarizes the process we chose to detect and eliminate outliers.

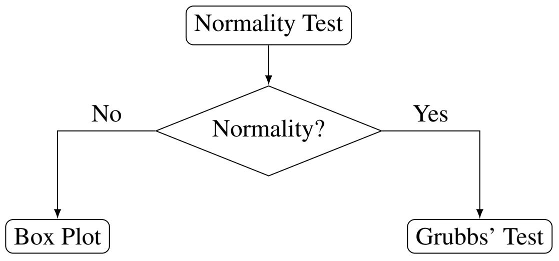


Figure 1: The outlier detection process.

Finally, the computation of $\gamma3$ and $\gamma2$ to evaluate the value of JB, so as the Grubb's and the Box Plot statistics calculus, are performed in parallel in the manner shown in Listing 1 (*cf.* Section 2). This in order to fasten the response times. Other statistics used in the next section are simultaneously collected here. Because the corresponding algorithm is very simple (the computation of each statistic is considered as a single task), we do not present it.

## 4 DISCRETIZATION METHODS

Discretization methods, so as outlier management methods, apply on columns of numerical values. However, in a previous work, we integrated also other types of column values, such as strings, by performing a kind of translation of such values (based on their frequency) into numerical ones (Ernst and Casali, 2011). This is why our approach, *a priori* dedicated to numerical values, can be easily extended to any given database.

The discretization of an attribute consists in finding *NbBins* disjoint intervals which will further represent it in a consistent way. The final objective of discretization methods is to ensure that the mining part of the KDD process generates efficient results. In our approach, we use only direct discretization methods in which *NbBins* must be known in advance and represents the upper limit for every column of the input data. *NbBins* was a parameter fixed by the end-user in the mentioned previous work above. As an alternative, the literature proposes several formulas (Rooks-Carruthers, Huntsberger, Scott, *etc.*) for computing such a number. Therefore we use the Huntsberger formula, the best from a theoretical point of view (Cauvin et al., 2008), and given by: $1+3.3\times log_{10}(N)$. We apply the formula on the non null values of each column.

### 4.1 Related Work

In this section, we only discuss the final discretization methods that have been kept for this work. This is because other implemented methods have not revealed themselves to be as efficient as expected (such as Embedded Means Discretization for example), or are otherwise not a worthy alternative to the presented ones (Quantiles based Discretization). The methods we use are: Equal Width Discretization (EWD), Equal Frequency Fisher-Jenks Discretization (EFD-Jenks), AVerage and STandard deviation based discretization (AVST), and K-Means. These methods, which are unsupervised and static (Mitov et al., 2009), have been widely discussed in the literature: See for example (Cauvin et al., 2008) for EWD and AVST, (Jenks, 1967) for EFD-Jenks, or (Kanungo et al., 2002), (Arthur et al., 2011) and (Jain, 2010) for KMEANS. For these reasons, we only summarize their main characteristics and their field of applicability in Table 1.

Let us underline that the computed *NbBins* value is in fact an upper limit, not always reached, depending on the applied discretization method. Thus, EFD-Jenks and KMEANS generate most of the times less than *NbBins* bins. This implies that other methods which generate the *NbBins* value differently, for example through iteration steps, may apply if *NbBins* can be upper bounded.

**Example 1.** *Let us consider the numeric attribute representing the weight of several persons* $SX = \{59.04, 60.13, 60.93, 61.81, 62.42, 64.26, 70.34, 72.89, 74.42, 79.40, 80.46, 81.37\}$. *SX contains 12 values, so by applying the Huntsberger's formula, if we aim to discretize this set, we have to use 4 bins.*

*Table 2 shows the bins obtained by applying all the discretization methods proposed in Table 1. Table 3 shows the number of values of SX belonging to each bin associated to every discretization method.*

*As it is easy to understand, we cannot find two discretization methods producing the same set of bins. As a consequence, the distribution of the values of SX is different depending on the method used.*

### 4.2 Discretization Methods and Statistical Characteristics

As seen in the last Section, when attempting to discern the best discretization method for a column, its shape is very important. We characterize the shape of a distribution according to four criteria: (*i*) Multimodal, (*ii*) Symmetric or Antisymmetric, (*iii*) Uniform, and (*iv*) Normal. This is done in order to deter-

Table 1: Summary of the discretization methods used.

| **Method** | **Principle** | **Applicability** |
|---|---|---|
| EWD | This simple to implement method creates intervals of equal width. | Not applicable for asymmetric or multimodal distributions. |
| EFD-Jenks | Jenks' method provides classes with, if possible, the same number of values while minimizing the internal variance of intervals. | The method is effective from all statistical points of view but presents algorithmic complexity in the generation of the bins. |
| AVST | Bins are symmetrically centered on the mean and have a width equal to the standard deviation. | Intended only for normal distributions. |
| KMEANS | Based on the Euclidean distance, the method determines a partition minimizing the quadratic error between the mean and the points of each interval. | One disadvantage of this method is its exponential complexity, so the computation time can be long. It is applicable to any form of distribution. |

Table 2: Set of bins associated to sample $SX$.

| Method | $Bin_1$ | $Bin_2$ | $Bin_3$ | $Bin_4$ |
|---|---|---|---|---|
| EWD | [59.04, 64.62[ | [64.62, 70.21[ | [70.21, 75.79[ | [75.79, 81.37] |
| EFD-Jenks | [59.04; 60.94] | ]60.94, 64.26] | ]64.26, 74.42] | ]74.42, 81.37] |
| AVST | [59.04; 60.53[ | [60.53, 68.65[ | [68.65, 76.78[ | [76.78, 81.37] |
| KMEANS | [59.04; 61.37[ | [61.37, 67.3[ | [67.3, 77.95[ | [77.95, 81.37] |

Table 3: Population of each bin of sample $SX$.

| Method | $Bin_1$ | $Bin_2$ | $Bin_3$ | $Bin_4$ |
|---|---|---|---|---|
| EWD | 6 | 0 | 3 | 3 |
| EFD-Jenks | 3 | 3 | 3 | 3 |
| AVST | 2 | 4 | 4 | 2 |
| KMEANS | 3 | 3 | 4 | 2 |

mine what discretization method(s) may apply. Some tests use statistics introduced in Section 3.2. More precisely, we perform the following tests, which have to be performed in the presented order:

**Multimodal Distributions:** We use the Kernel method presented in (Silverman, 1986) to characterize multimodal distributions. The method is based on estimating the density function of the sample by building a continuous function, and then calculating the number of peaks using its second derivative. It involves building a continuous density function, which allows us to approximate automatically the shape of the distribution. The multimodal distributions are those which have a number of peaks greater than 1.

**Symmetric and Antisymmetric Distributions:** To characterize antisymmetric distributions in a next step, we use the Skewness, noted $\gamma_3$ (*cf.* Equation (5)). The distribution is symmetric if $\gamma_3 = 0$. Practically, this rule is too exhaustive, so we relaxed it by imposing limits around 0 to set a fairly tolerant rule which allows us to decide whether a distribution is considered antisymmetric or not. The associated method is based on a statistical test. The null hypothesis is that the distribution is symmetric.

Consider the statistic: $T_{Skew} = \frac{N}{6}(\gamma_3^2)$. Under the null hypothesis, $T_{Skew}$ follows a law of $\chi^2$ with one degree of freedom. In this case, the distribution is antisymmetric if $\alpha = 5\%$ if $T_{Skew} > 3.8415$.

**Uniform Distributions:** We use then the normalized Kurtosis, noted $\gamma_2$, to measure the peakedness of the distribution or the grouping of probability densities around the average, compared with the normal distribution. When $\gamma_2$ (*cf.* Equation (6)) is close to zero, the distribution has a normalized peakedness: A statistical test is used again to automatically decide whether the distribution has normalized peakedness or not. The null hypothesis is that the distribution has a normalized peakedness.

Consider the statistic: $T_{Kurto} = \frac{N}{6}(\frac{\gamma_2^2}{4})$. Under the null hypothesis, $T_{Kurto}$ follows a law of $\chi^2$ with one degree of freedom. The null hypothesis is rejected at level of significance $\alpha = 0.05$ if $T_{Kurto} > 6.6349$.

**Normal Distributions:** We use the Jarque-Bera test (*cf.* Equation (4)).

These four successive tests allow us to characterize the shape of the (density function of the) distribution of each column. Combined with the main characteristics of the discretization methods presented in the last section, we get Table 4: This summarizes which discretization method(s) can be invoked depending on specific column statistics.

**Example 2.** *Continuing Example 1, the Kernel Density Estimation method (Zambom and Dias, 2012) is used to build the density function of sample SX (cf. Figure 2).*

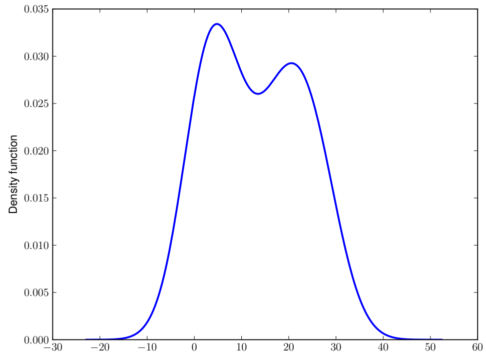


Figure 2: Density function of sample *SX* using Kernel Density Estimation.

*As we can see, the density function has two modes, is almost symmetric and normal. Since the density function is multimodal, we should stop at this step. But, as shown in Table 4, only EFD-Jenks and KMEANS produce interesting results according to our proposal. For the need of this example, let us perform the other tests. Since* $\gamma_3 = -0.05$*, the distribution is almost symmetric. As mentioned in Section 4.2, it depends on the threshold fixed if we consider that the distribution is symmetric or not. The distribution is not antisymmetric because* $T_{Skew} = 0.005$*. The distribution is not uniform since* $\gamma_2 = -1.9$*. As a consequence,* $T_{Kurto} = 1.805$*, and we have to reject the uniformity test. The Kolmogorov-Smirnov test results indicate that the probability that the distribution follows a normal law is 86.9% with* $\alpha = 0.05$*. Here again, accepting or rejecting the fact that we can consider if the distribution is normal or not depends on the fixed threshold.*

## 4.3 A Multi-criteria Approach for Finding the Best Discretization Method

Discretization must keep the initial statistical characteristics so as the homogeneity of the intervals, and reduce the size of the final data produced. So the discretization objectives are many and contradictory. For this reason, we chose a multi-criteria analysis to evaluate the available applicable methods of discretization. We use three criteria:

1. **Entropy ($H$):** The entropy $H$ measures the uniformity of intervals. The higher the entropy, the more the discretization is adequate from the viewpoint of the number of elements in each interval:

$$H = -\sum_{i=1}^{NbBins} p_i \log_2(p_i) \tag{7}$$

   where $p_i$ is the number of points of interval i divided by the total number of points ($N$), and $NbBins$ is the number of intervals. The maximum of $H$ is computed by discretizing the attribute into $NbBins$ intervals with the same number of elements. In this case, $H$ reduces to $log_2(NbBins)$.

2. **Index of Variance ($J$):** Which was introduced in (Lindman, 2012), measures the interclass variances proportionally to the total variance. The closer the index is to 1, the more homogeneous the discretization is:

$$J = 1 - \frac{\text{Intra-intervals variance}}{\text{Total variance}} \tag{8}$$

3. **Stability ($S$):** Corresponds to the maximum distance between the distribution functions before and after discretization. Let $F_1$ and $F_2$ be the attribute distribution functions respectively before and after discretization:

$$S = sup_x(|F_1(x) - F_2(x)|) \tag{9}$$

The goal is to find solutions that present a compromise between the various performance measures. The evaluation of these methods should be done automatically, so we are in the category of *a priori* approaches where the decision-maker intervenes just before the evaluation process step.

Aggregation methods are among the most widely used methods in multi-criteria analysis. The principle is to reduce to a unique criterion problem. In this category, the weighted sum method involves building a unique criterion function by associating a weight to each criterion (Roy and Vincke, 1981), (Clímaco, 2012) and (Pardalos et al., 2013). This method is limited by the choice of the weight, and requires comparable criteria. The method of inequality constraints is to maximize a single criterion by adding constraints to the values of the other criteria (Zopounidis and Pardalos, 2010). Its disadvantage is the choice of the thresholds of the added constraints.

Table 4: Applicability of discretization methods = f(distribution's shape).

| | Normal | Uniform | Symmetric | Antisymmetric | Multimodal |
|---|---|---|---|---|---|
| EWD | * | * | * | | |
| EFD | * | * | * | * | * |
| AVST | * | | | | |
| KMEANS | * | * | * | * | * |

For these reasons, we chose the method that minimizes the Euclidean distance from the target point ($H = log_2(NbBins)$, $J = 1$, $S = 0$).

**Definition 1.** *Let D be an arbitrary discretization method, and $V_D$ a measure of segmentation quality using the specified multi-criteria analysis:*

$$V_D = \sqrt{(H_D - log_2(NbBins))^2 + (J_D - 1)^2 + S_D^2} \quad (10)$$

The following proposition is the main result of this article: It indicates how we chose the best method among all the available and applicable ones.

**Proposition 1.** *Let DM be a set of discretization methods; the one, noted $\mathbb{D}$, that minimizes $V_D$ (see Equation (10)), $\forall D \in \{DM\}$, is the most appropriate discretization method.*

**Example 3.** *Continuing Example 1, Table 5 shows the evaluation results for all the discretization methods at disposal. Let us underline that for the need of our example, all the values are computed for every discretization method, and not only for the ones which should have been selected after the step proposed in Section 4.2 (cf. Table 4).*

Table 5: Evaluation of discretization methods.

| | $H$ | $J$ | $S$ | $V_{DM}$ |
|---|---|---|---|---|
| EWD | 1.5 | 0.972 | 0.25 | 0.313 |
| EFD-Jenks | 2 | 0.985 | 0.167 | 0.028 |
| AVST | 1.92 | 0.741 | 0.167 | 0.101 |
| KMEANS | 1.95 | 0.972 | 0.167 | 0.031 |

*The results show that EFD-Jenks and KMEANS are the two methods that obtain the lowest values for $V_D$. The values got by the EWD and AVST methods are the worst: This is consistent with the optimization proposed in Table 4, since the sample distribution is multimodal.*

As a result of Table 4 and of Proposition 1, we define the POP (Parallel Optimized Preparation of data) method, see Algorithm 1. For each attribute, after constructing Table 4, each applicable discretization method is invoked and evaluated in order to keep finally the most appropriate. The content of these two tasks (three when involving the statistics computations) are executed in parallel using the *parallel_invoke* template (*cf.* Section 2).

**Algorithm 1:** POP: Parallel Optimized Preparation of Data.

```
Input: $X$ set of numeric values to discretize,
       DM set of discretization methods
       applicable
Output: Best set of bins for $X$
1  Parallel_Invoke For each method $D \in$ DM do
2      Compute $\gamma_2$, $\gamma_3$ and perform Jarque-Bera
       test;
3  end
4  Parallel_Invoke For each method $D \in$ DM do
5      Remove $D$ from DM if it does not satisfy
       the criteria given in Table 4;
6  end
7  Parallel_Invoke For each method $D \in$ DM do
8      Discretize $X$ according to $D$;
9      $V_D =$
       $\sqrt{(H_D - log_2(NbBins))^2 + (J_D - 1)^2 + S_D^2}$;
10 end
11 $\mathbb{D} = argmin(\{V_D, \forall D \in DM\})$;
12 return set of bins obtained line 8 according to
   $\mathbb{D}$
```

## 5 EXPERIMENTAL ANALYSIS

In this section, we present some experimental results by evaluating three samples. We decided to implement POP using the MineCor KDD software when mining Correlation Rules (Ernst and Casali, 2011), and using R Project when searching for Association Rules. $Sample_1$ is a randomly generated file that contains heterogeneous values. $Sample_2$ and $Sample_3$ correspond to real data representing measurements provided by a microelectronics manufacturer (STMicroelectronics) after completion of the front-end process. This is because the applicative aspect of our work is to determine in this domain what parameters have the most impact on a specific parameter, the yield (*a posteriori* process control). So if the proposed datasets seem a bit small, they correspond to

Table 6: Characteristics of the databases used.

| Sample | Number of columns | Number of rows | Type |
|---|---|---|---|
| $\text{Sample}_1$ | 10 | 468 | generated |
| $\text{Sample}_2$ | 1281 | 296 | real |
| $\text{Sample}_3$ | 8 | 727 | real |

effective data on which we perform mining. Table 6 summarizes the characteristics of the samples.

Experiments were performed on a 4 core computer (a DELL Workstation with a 2.8 GHz processor and 12 Gb RAM working under the Windows 7 64 bits OS). First, let us underline that we shall not focus in this section on performance issues. Of course, we have chosen to parallelize the underdone tasks in order to improve response times. As it is easy to understand, each of the *parallel_invoke* loops has a computational time which is closed to the most consuming calculus inside of each loop. Parallelism allows us to compute and then to evaluate different "possibilities" in order to chose the most efficient one for our purpose. This, without waste of time, when comparing to a single "possibility" processing. Moreover, we can easily add other tasks to each loop (statistics computations, discretization methods, evaluation criteria), the last assertion remains true. Some physical limits exist: No more then seven tasks can be launched simultaneously within the 2010 C++ Microsoft .NET / PPL environment. And each individual described task does not require more than a few seconds to execute, even on the $\text{Sample}_2$ database.

Concerning outlier management, we recall that in the previous versions of our software, we used the single standardization method with $p$ set by the user (Ernst and Casali, 2011). With the new approach presented in Section 3.2, we notice an improvement in the detection of true positive or false negative outliers by a factor of 2%.

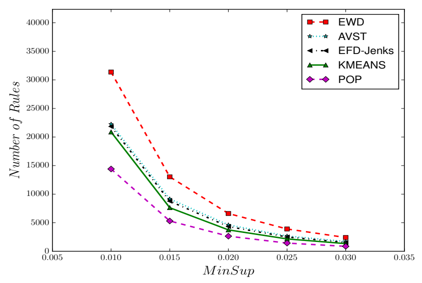
We focus hereafter on experiments performed in order to compare the different available discretization methods on the three samples. Figures 3(a), 4(a) and 5(a) reference various experiments when mining Association Rules. Figures 3(b), 4(b) and 5(b) correspond to experiments when mining Correlation Rules. When finding Association Rules, the minimum confidence ($MinConf$) threshold has been arbitrarily set to 0.5. The different figures provide the number of Association or of Correlation Rules respectively while the minimum support ($MinSup$) threshold varies. Each figure is composed of five curves: One for each of the four discretization methods presented in Table 4, and one for our global method (POP). Each method is individually applied on each column of the considered database.

Analyzing the Association Rules detection process, experiments show that POP gives the best results (few number of rules), and EWD is the worst. Using real data, the number of rules is reduced by a factor comprised between 5% and 20%. This reduction factor is even better using synthetic (generated) data and a low $MinSup$ threshold. When mining Correlation Rules on synthetic data, the method which gives the best results with high thresholds is KMEANS while it is POP when the support is low. This can be explained by the fact that the generated data are sparse and multimodal. When examining the results on real databases, POP gives good results. However, let us underline that the EFD-Jenks method produces unexpected results: Either we have few rules (Figures 3(a) and 3(b)), or we have a lot (Figures 4(a) and 4(b)) with a low threshold. We suppose that the high number of used bins is at the basis of this result.

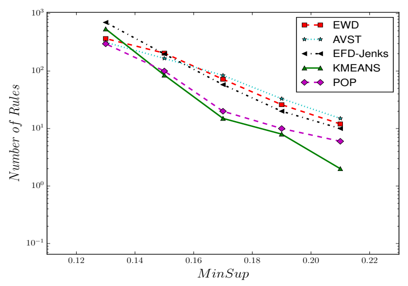
## 6 CONCLUSION AND FUTURE WORK

In this paper, we presented a new approach for automatic data preparation: No parameter has to be provided by the end-user. This step is generally split into two sub-steps: (*i*) detecting and eliminating outliers, and (*ii*) applying a discretization method in order to transform any column into a set of bins. We show that the detection of outliers is depending on if data distribution is normal or not. As a consequence, the same pruning method is not applied (Box plot *vs.* Grubb's test). Moreover, when trying to find the best discretization method, what is important is not the law followed by the column, but the shape followed by its distribution law. This is why we propose an automatic choice to find the most appropriate discretization method based on a multi-criteria approach. Experimental evaluations performed using real and synthetic data validate our approach showing that we can reduce the number of Association and of Correlation Rules using an adequate discretization method.

For future works, we aim (*i*) To add other discretization methods (Khiops, Chimerge, Fayyad-

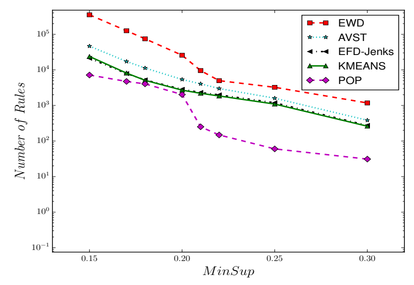


(a) Results for APriori

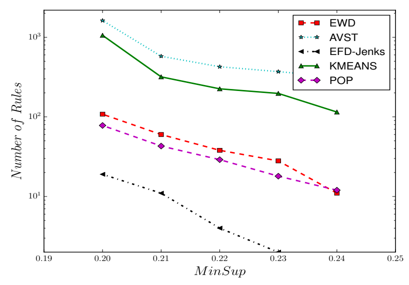


(b) Results for MineCor

Figure 3: Execution on Sample$_1$.

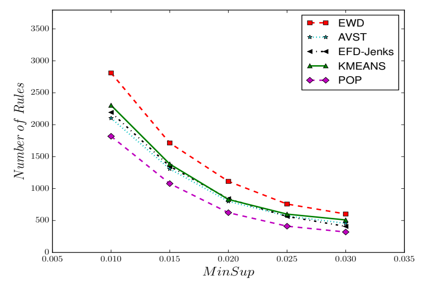


(a) Results for APriori

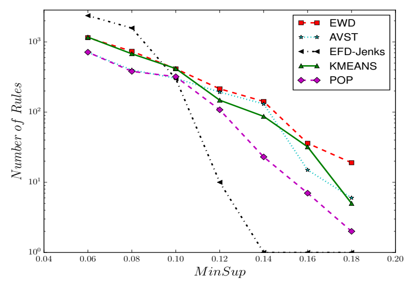


(b) Results for MineCor

Figure 4: Execution on Sample$_2$.



(a) Results for APriori



(b) Results for MineCor

Figure 5: Execution on Sample$_3$.

Irani, *etc.*) to our system, (*ii*) To measure the quality of the obtained rules using classification methods (based on association rules or decision trees), (*iii*) To apply our methodology with other data mining techniques (decision tree, SVM, neural network) and (*iv*) To perform more experiments using other databases.

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