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Contextual classification for smart machining based on unsupervised machine learning by Gaussian mixture model

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ABSTRACT

Intelligent machine-tools generate a large amount of digital data. Data mining can support decision making for operational management. The first step in a data mining approach is the selection of relevant data. Raw data must, therefore, be classified into different groups of contexts. This paper proposes an original contextual classification of data for smart machining based on unsupervised machine learning by Gaussian mixture model. The optimal number of classes is determined by the silhouette method based on the Bayesian information criterion. This method is validated on real data from four different machine-tools in the aerospace industry. Manual data mining and k-fold cross validation confirm that the proposed method provides good contextual classification results. Then, several key performance indicators are calculated using this contextual classification. They show the relevancy of the approach.

KEYWORDS

Industry 4.0, machining, unsupervised machine learning, GMM, BIC.

1. Introduction

High-Speed Machining (HSM) has significantly increased spindle speed compared to conventional machining. Production systems are very flexible, especially in the aeronautics industry, where hundreds of tools machine several thousands of parts with different references on the same site. It is not easy for the Manufacturing Department to identify problematic programs or tools. The main problems are chatter (instability during machining), tool breakage and over-vibrations. Therefore, a data mining system is necessary to protect the machine-tool and work-pieces (especially for aeronautical parts which present high value-added). Teti et al. (2010) make an overview of the existing techniques of machining monitoring and list all measurable and studied defects. Maleki et al. (2017) proposed a FMEA-based approach for the choice of the sensors. Quintana and Ciurana (2011) focus on the state of the art on chatter and existing methods to detect and to avoid it. Zhou and Xue (2018) make a summary of the methods used to monitor tool wear in milling processes, including sensors, feature extraction and monitoring models. Godreau et al. (2019) propose a vibration criterion for the detection of chatter, a source of non-quality.

In the general context of Industry 4.0, large volumes of manufacturing data are available on instrumented machine-tool. They are interesting to exploit not only to improve machine-tool performance but also to support the decision making of operational

management. Lenz, Wuest, and Westkämper (2018) propose a holistic approach to machining data analysis in order to combine tasks and to group analysis objectives among different departments within the company. Morgan and O'Donnell (2018) present the design and development of a cyber-physical process monitoring system for machine-tool. Liu et al. (2018) propose a systematic development method for machine-tool 4.0. In order to extract data from databases more efficiently and accurately, contextual classification is necessary to understand the status of the machine-tool and to realize a more relevant calculation of Key Performance Indicators (KPI). Many researches propose the use of machine learning algorithms directly on the raw data (machine-tool signals). However, few researches focus on data pre-processing to identify the context. In this article, machine learning algorithms for contextual classification are developed. They will permit a more relevant calculation of Key Performance Indicators.

Machine Learning is a field of Artificial Intelligence that relies on statistical approaches. It can be applied to machine-tool signals analysis. Kim et al. (2018) list and summarize machining contributions using machine learning algorithms. There are two categories: supervised and unsupervised machine learning.

- *Supervised machine learning* learns to classify from already labeled output samples. It aims at making correct predictions on the data which is not present in the learning set. For example, El-Mounayri and Deng (2010) designed and implemented a neural networks (ANN) for force prediction to optimize the cutting parameters in optimizing $2^{1/2}$ - axis milling; C. Zhang and H. Zhang (2016) show that the least squares support vector machine (SVM)-based tool wear model is suitable to predict tool wear at certain range of cutting conditions in milling operation; Rodríguez et al. (2017) propose a decision-making tool based on decision trees for roughness prediction in face milling.
- *Unsupervised machine learning* learns to classify unlabeled data. There are different types of unsupervised learning: K-means, hierarchical classification (ascending or descending), distribution density estimates (*e.g.*, Gaussian Mixing Model - GMM). Bhinge et al. (2014) build an energy prediction model when machining a component using the Gaussian regression algorithm. Godreau et al. (2019) calculate the criteria thresholds by applying the Maximum Likelihood Estimation method.

In industry, it is challenging to collect labeled output data. As a result, most industrial applications use unsupervised machine learning methods. In a previous study, Wang et al. (2019) compared the different methods of unsupervised machine-learning, and Gaussian Mixture Model (GMM) was the most effective for contextual classification. Another challenge of smart-machining comes from the management of time series; the state of the machine can change whenever and has to be identified every tenth of a second.

In this article, unsupervised machine learning by Gaussian Mixture Model (GMM) is used. GMM is a statistical tool used to parametrically estimate the distribution of random variables by modeling them as a mixture of Gaussian distributions (Reynolds 2015). The distributions' parameters are estimated from the learning data using the Maximization Expectation algorithm. The main advantage of GMM is that it can correctly classify data with unbalanced classes, while its disadvantage is that the results of GMM directly depend on the choice of parameters. An additional algorithm can therefore be useful to determine the necessary number of classes automatically (Schwarz et al. 1978). The Bayesian Information Criterion (BIC) is particularly recommended.

This paper proposes an original contextual classification of data for smart machining

based on unsupervised machine learning by Gaussian mixture model. The method is applied to four machining databases collected in the aeronautics industry. The number of classes is determined by the BIC method. The classifications are then evaluated using manual data mining and k-fold validation. This paper is organized as follows. Section 2 introduces the framework of the study as well as the contextual classification method. Section 3 proposes the method based on Gaussian Mixture Model (GMM). The next section depicts the silhouette method, which determines the optimal number of classes. Section 5 applies the proposed method to vibration signals and power signals to know whether the tool is cutting materials or not. Section 6 verifies the obtained classification using manual data mining and k-fold cross-validation. Section 7 presents KPIs based on the obtained contextual classification. These indicators will aid decision-making within the company.

2. Data analysis process

2.1. Framework of the study

The work presented in this article is a part of the ANR SmartEmma project, which aims at developing intelligent and connected machine-tools. Fig. 1(a) shows an overview of the road-map of this project. A device, called Emmatools, collects the measured data during machining and stores it in a database (De Castelbajac et al. 2014). It is installed on machine-tools in factories of aircraft manufacturers. Fig. 1(b) presents the schematic diagram of the Emmatools. It collects data every tenth of a second. The data comes from two information sources: the Computer Numerical Control (CNC) and the added sensors. By field bus, the CNC provides machining context data such as the tool name, the current program, machine, and spindle motions. The sensors integrated into the machine-tool collect the instantaneous power of the spindle, temperatures, as well as the vibrations from 4 accelerometers integrated into the spindle (radially at each bearing).

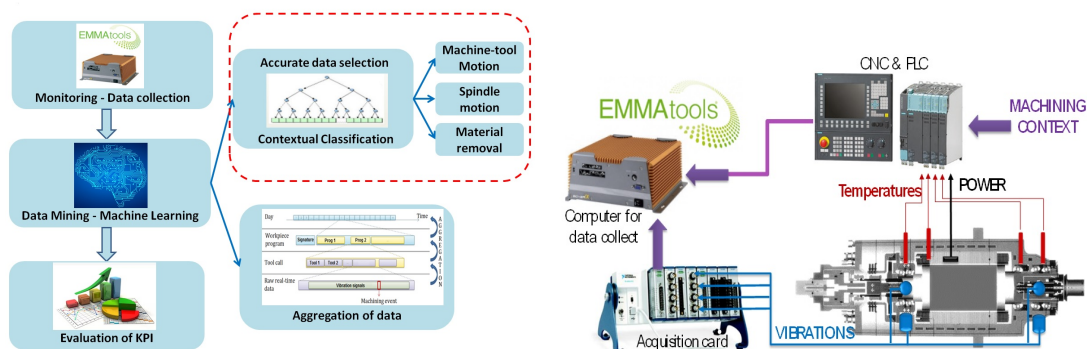


Figure 1. Data mining process for machining (a) and schematic diagram of the data collect device (b)

The machine learning methods will be developed on the one hand to perform contextual classifications, and on the other, to aggregate the data. The latter concept can be found in Ritou et al. (2019), which proposes a method to address the issue of data volume using multi-level aggregation. 1 GB of data is collected per day and per machine-tool. Contextual classification permits to classify raw data into ordered and meaningful forms. Using this contextual information, noise is reduced and relevant KPIs can be calculated. Those KPIs support decisions on the HSM process and the

global management of the company.

2.2. Contextual classification method

As previously mentioned, contextual classification enables a more relevant evaluation of KPIs. In the context of our research work, it is interesting to know:

- if the spindle is stopped (S) or rotating at constant speed (CS) or varying speed (VS);
- if the machine-tool is stopped or moving at constant or varying speed;
- if the tool is cutting materials or not (N), with a constant (CC) or varying tool engagement (CV).

From these three contextual information, 17 potential states for the machine-tool can be defined (cf. Table 1). The objective is to determine the state of the machine-tool at each instant. Indeed, it will enable accurate data selection and analyses dedicated to the considered state.

Table 1. Classification of the different states of the machine-tool

		Feed rate of the machine-tool Vf						
		Vf=0	Vf>0					
			$\Delta Vf > T_{\Delta Vf}$			$\Delta Vf \leq T_{\Delta Vf}$		
			$Arms \leq T_{Arms}$ & $P \leq P_{idle}$	$Arms > T_{Arms}$ or $P > P_{idle}$		$Arms \leq T_{Arms}$ & $P \leq P_{idle}$	$Arms > T_{Arms}$ or $P > P_{idle}$	
		$\Delta P \leq T_{\Delta P}$	$\Delta P > T_{\Delta P}$			$\Delta P \leq T_{\Delta P}$	$\Delta P > T_{\Delta P}$	
Spindle speed N	N=0	Spindle: S Machine: S Cutting: N	Spindle: Stopped (S) Machine-tool: Varying Speed (VS) Cutting: No (N)			Spindle: Stopped (S) Machine-tool: Constant Speed (CS) Cutting: No (N)		
	N>0	Spindle: VS Machine: S Cutting: N	Spindle: VS Machine: VS Cutting: N	Spindle: VS Machine: VS Cutting: eng ^a . Constant (CC)	Spindle: VS Machine: VS Cutting: eng. Varying (CV)	Spindle: VS Machine: CS Cutting: N	Spindle: VS Machine: CS Cutting: eng. Constant (CC)	Spindle: VS Machine: CS Cutting: eng. Varying (CV)
	$\Delta N \leq T_{\Delta N}$	Spindle: CS Machine: S Cutting: N	Spindle: CS Machine: VS Cutting: N	Spindle: CS Machine: VS Cutting: CC	Spindle: CS Machine: VS Cutting: CV	Spindle: CS Machine: CS Cutting: N	Spindle: CS Machine: CS Cutting: CC	Spindle: CS Machine: CS Cutting: CV

^aTool cutting with constant tool engagement

These classifications will be performed focusing on a variable X (e.g., feed rate Vf , spindle speed N or spindle power P) and also on the variation of X , noted ΔX (e.g., ΔVf or ΔN), which is defined by the simple derivative:

$$\Delta X = \frac{X_n - X_{n-1}}{\Delta t} \quad (1)$$

where, X_n is the n^{th} measure; X_{n-1} is the measure at the previous instant and Δt is the data recording period (0.1s). The objective is to calculate a classification threshold $T_{\Delta X}$ by unsupervised machine learning methods. A previous study (Wang et al. 2019) compared the performance of GMM with the k-means method; GMM performs better in this context of research work. The classifications are then carried out based on the following rules:

- There are three clusters for machine-tool movements: stopped ($Vf = 0$), moving at constant speed ($Vf > 0$ and $\Delta Vf \leq T_{\Delta Vf}$), or varying speed ($Vf > 0$ and $\Delta Vf > T_{\Delta Vf}$);
- There are three clusters for spindle rotation: stopped ($N = 0$); rotating at con-

stant speed ($N > 0$ and $\Delta N \leq T_{\Delta N}$); or varying speed ($N > 0$ and $\Delta N > T_{\Delta N}$).

In order to know if the tool is cutting materials or not, a classification according to the criteria $Arms$ (root mean square-RMS of vibration acceleration value, in m/s^2) and the spindle power P (kW) is proposed, when the machine is moving (feedrate $Vf > 0$). In machining, it is known that if the tool is cutting, its vibration ($Arms$) is greater than if the tool is not cutting. It is also known that when the tool is not cutting, the power (P) will exceed the spindle power corresponding to idle rotation (P_{idle}). However, there is a subclass called *spindle startup* where the $Arms$ is also greater due to the lubrication spindle startup. This subclass should be identified and assigned to the cluster *tool not cutting*. The proposed business rules are:

- if ($P > P_{idle}$ or $Arms > T_{Arms}$) and $Vf > 0$, except the subclass *spindle startup*, the tool is cutting material;
- if $P \leq P_{idle}$ and $Arms \leq T_{Arms}$, including the subclass *spindle startup*, the tool is not cutting material.

The following procedure aims to check if the GMM classifications are correct or not:

- Modeling : The contextual classification thresholds are determined, using GMM on different descriptors (ΔN , ΔVf , $Arms$, P and ΔP). Each machine-tool has different characteristics, so it is necessary to perform an initial training for each machine-tool. One-day data of a machining database is used for this purpose.
- Classifying: The classifications are carried out using GMM threshold and the business rules.
- Validation: The quality of classifications is assessed by confusion matrix, using a vector labeled with actual classes of machine-tool states.

3. Gaussian Mixture Model

The Gaussian Mixture Model is a statistical model used to parametrically estimate the distribution of random variables by modeling them as a mixture of Gaussian distributions. It has been used in several areas such as audio recognition, measurement error modeling (Huang et al. 2005). The principle of GMM is to find an approximation of the probability density f from a sample of n observations of the random vector $X = \{x_1, x_2, x_3 \dots x_n\}$ (where each observation x_i is assumed independent) using a linear combination of several Gaussian components.

To evaluate the quality of the model parameter θ , the probability density associated with the observed data is calculated (Maugis, Celeux, and Martin-Magniette 2009):

$$f(X, \theta) = \sum_{j=1}^k a_j N_j(x_i | \mu_j, \sigma_j) \quad (2)$$

where, k is the number of Gaussian; a_j is the weight of the j^{th} Gaussian. It verifies the probability conditions such as $\sum_{j=1}^k a_j = 1$, and $0 \leq a_j \leq 1$; $N_j(x_i | \mu_j, \sigma_j)$ expresses the probability that a measure x_i is associated with the j^{th} Gaussian. In this context, the parameters of the model are collectively represented as $\theta = \{a_j, \mu_j, \sigma_j\}$.

In the literature, there are several methods for estimating these GMM parameters. In the present paper, the Maximum Likelihood method is used to determine the parameters θ .

The main idea of Maximum Likelihood Estimation (MLE) is to find a set of parameter estimates, so that the likelihood of the sample used is maximized. Since the n observations are independent, the likelihood function $L(X|\theta)$ can be written as (Bishop 2006):

$$L(X|\theta) = f(x_1, \theta) \times f(x_2, \theta) \times \cdots \times f(x_n, \theta) = \prod_{i=1}^n f(x_i, \theta) \quad (3)$$

Then substitute Eq. (2) into Eq. (3) leads to:

$$L(X|\theta) = \prod_{i=1}^n \sum_{j=1}^k a_j N_j(x_i|\mu_j, \sigma_j) \quad (4)$$

It is easier to maximize log-likelihood than the likelihood function itself. The log-likelihood function is written as:

$$\ln L(X|\theta) = \sum_{i=1}^n \ln \left(\sum_{j=1}^k a_j N_j(x_i|\mu_j, \sigma_j) \right) \quad (5)$$

The problem of estimation by the maximum likelihood method is therefore to find the roots of the following equation:

$$\frac{\partial \ln L(X|\theta)}{\partial \theta} = 0 \quad (6)$$

In general, maximizing the likelihood function does not have an analytical solution. It is then necessary to use iterative methods. The most common is to use the EM algorithm (Expectation-Maximization) (Feng, Lai, and Kar 2016). However, the EM algorithm needs initial parameters; the most important of them is the number of classes k .

In general, the larger the number of parameters to be estimated into the model, the better the model approaches to the data. However, the complexity of the computation will also increase when there are too many parameters to be estimated. Therefore, a compromise must be found; this is the goal of the the Bayesian Information Criterion (BIC). The BIC is defined as follow (Schwarz et al. 1978):

$$BIC(k) = 2 \times \text{Max}(\ln(L(X|\theta))) - N_m \ln(n) \quad (7)$$

where, $\text{Max}(\ln(L(X|\theta)))$ is the maximized log-likelihood function, N_m is the number of parameters to be estimated in this model (3 per Gaussian: weight, mean and standard deviation), n is the number of observations, and k is the number of classes. In the BIC, the term (N_m) penalizes the complexity of the model. Therefore, BIC is maximized for most parsimonious setting, *i.e.*, with small N_m , and larger likelihood. Consequently, BIC is a good indicator to determine the number of classes required.

4. Validation of the Gaussian model by silhouette method

In this section, the previously proposed machine learning procedure by GMM is applied to database from four different machine-tools in two factories producing aeronautical structural parts:

- The machine-tool #1 is a Forest Aeromill for aluminum machining, in company #A;
- The machine-tool #2 is a Forest Aerostar for aluminum machining, in company #A;
- The machine-tool #3 is a Mazak Mazatrol for aluminum machining, in company #B;
- The machine-tool #4 is a Mazak i800T for titanium machining, in company #B.

An Emmatools device was installed on each machine-tool, and the machining data were collected for months during industrial productions. The classifications should determine:

- If the spindle is rotating (at constant or varying speed) or not, according to the classification on the descriptor ΔN ;
- If the machine-tool is moving (at constant or varying speed) or not, according to the classification on the descriptor ΔVf ;
- If the tool is removing materials (with constant or varying tool engagement) or not, according to the classification descriptor of $Arms$, P and ΔP .

For each machine-tool, the determination of the number of context classes is crucial and required for the Gaussian model that follows (in order to identify the classification thresholds for the business rules). The proposed method is:

- Apply GMM for each descriptor (ΔN , ΔVf , $Arms$, P and ΔP) for different numbers of classes (1, 2, ..., k). For each number of classes, a BIC value can be determined according to Eq. (7), in order to evaluate the model.
- Compute the BIC in relation to the number of classes for each descriptor. In the present case, each BIC value converges to a maximum.
- Chose the minimal number of context classes required

In this paper, a class number based on 90% of the BIC maximum is chosen. In this way, the class number is reduced and enables better interpretability of the results.

4.1. *Silhouette method on the variation of spindle speed*

The Gaussian model analyzed by BIC on the variation of spindle speed ΔN is done on the four machine-tools. Fig. 2 shows the results: the BIC value reaches 90% of the BIC maximum with 2 classes. Thus, ΔN was classified into 2 classes, 2 clusters that correspond to the constant and varying spindle rotation. The experimental data confirm what was assumed in Table 1.

4.2. *Silhouette method on the variation of axis speed*

The Gaussian model analyzed by BIC on the variation on ΔVf are performed on four machine-tools as shown in Fig. 3. The figure shows that the BIC value reaches 90% of the BIC maximum with 2 classes. Thus, ΔVf was classified into 2 classes, 2 clusters

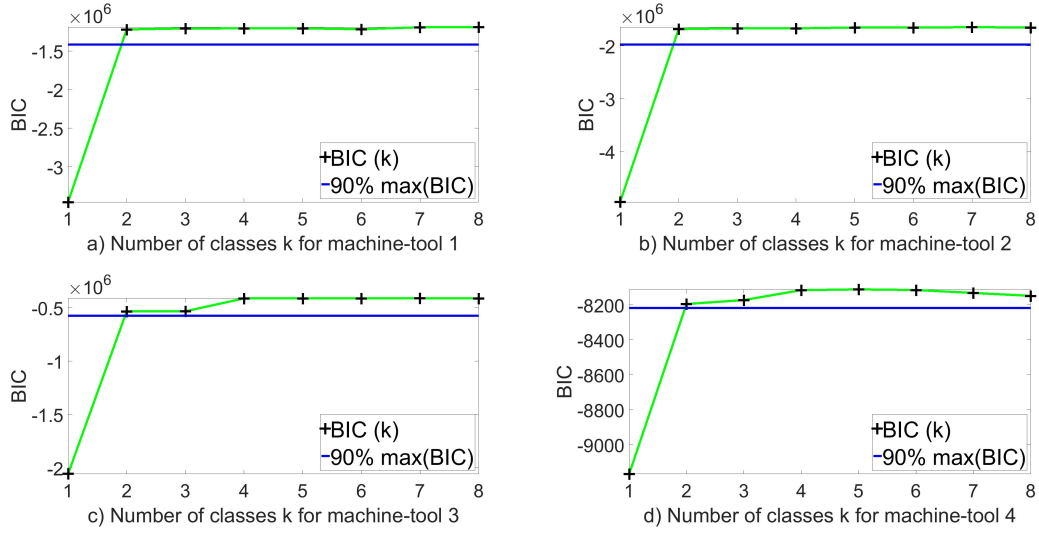


Figure 2. BIC on ΔN issued from the 4 machine-tools

that correspond to constant and varying motion of the machine-tool.

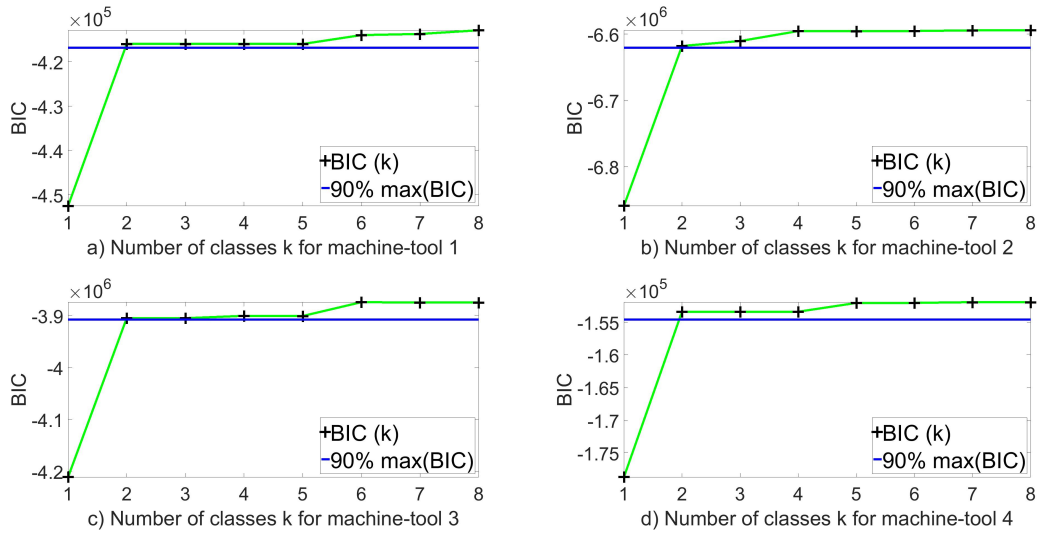


Figure 3. BIC on ΔVf issued from the 4 machine-tools

4.3. Silhouette method on vibrations and power

The descriptors $Arms$ (vibration) and P (spindle power) are used to determine if the tool is removing materials or not (cf. 1). To determine the number of classes required, Gaussian model analyses by BIC on $Arms$ as shown in Fig. 4 and P Fig. 5. 4 different machine-tools are used in order to validate the results.

The figure shows that the BIC value reaches 90% of the BIC maximum with 3 classes. Thus, $k=3$ and the vibrations $Arms$ and the power P were classified into 3 classes. The 3 classes are interpreted as: not cut, low material removal and high material removal.

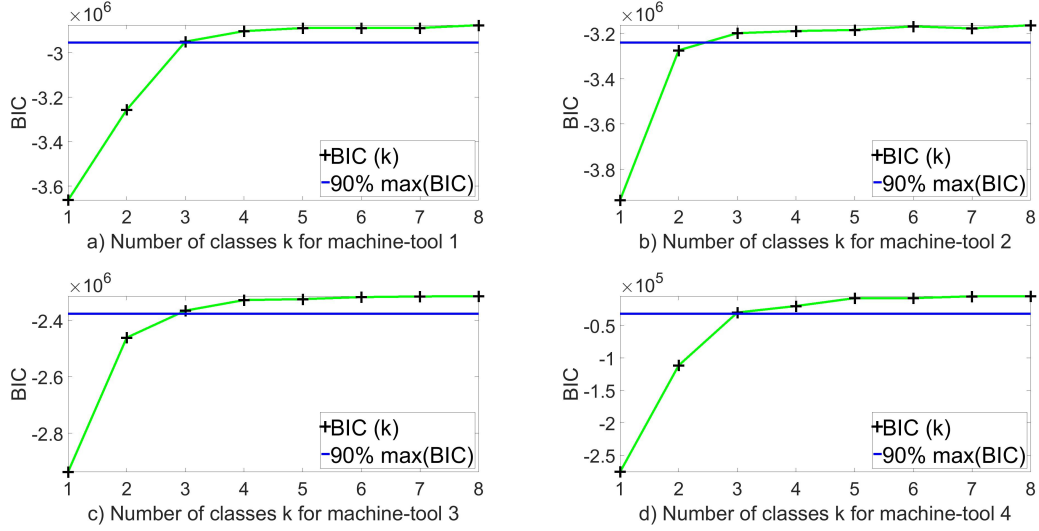


Figure 4. BIC on *Arms* (when N constant et $Vf > 0$) issued from the 4 machine-tools

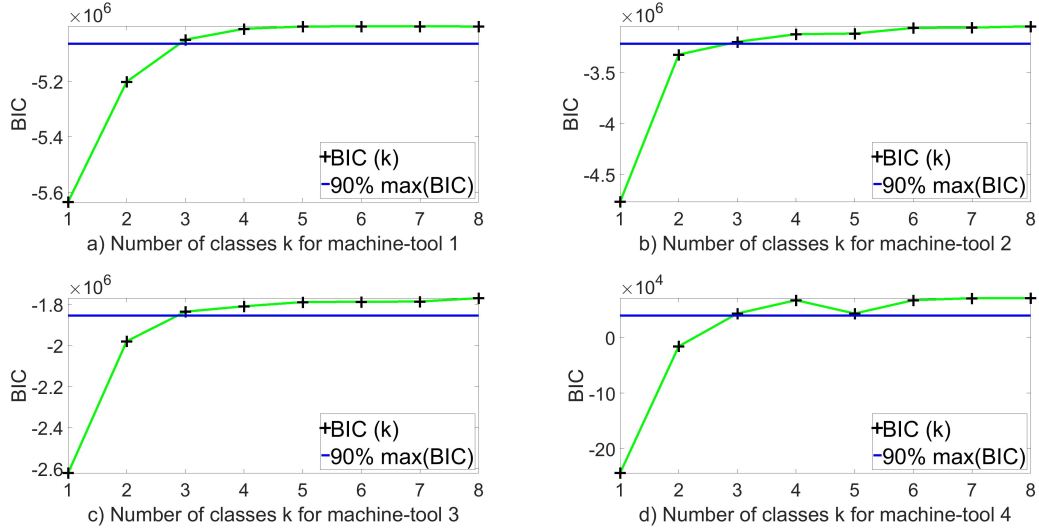


Figure 5. BIC on P (when N constant et $Vf > 0$) issued from the 4 machine-tools

5. Contextual classification of the material removal

Once the class number determined by BIC, the classification thresholds are identified from one-day data by GMM. Then, the business rules are applied, leading to the classification. This section presents the classification. GMM is applied to the collected data in the context of *spindle rotation at constant speed* and *axis motion ($Vf > 0$)* see Table 1. Two datasets illustrate the approach: machine-tools #2 and #3 for aluminum machining.

5.1. Modeling and classification for machine-tool #3

The distribution of *Arms* in this class (N constant and $Vf > 0$) is modeled by 3 Gaussians (see section 4).

- a Gaussian represents the class *tool not cutting* (Y1 green),
- another the class *tool cutting* (Y3 blue),
- the 3rd Gaussian represents '*severe machining vibrations*' (Y2 red).

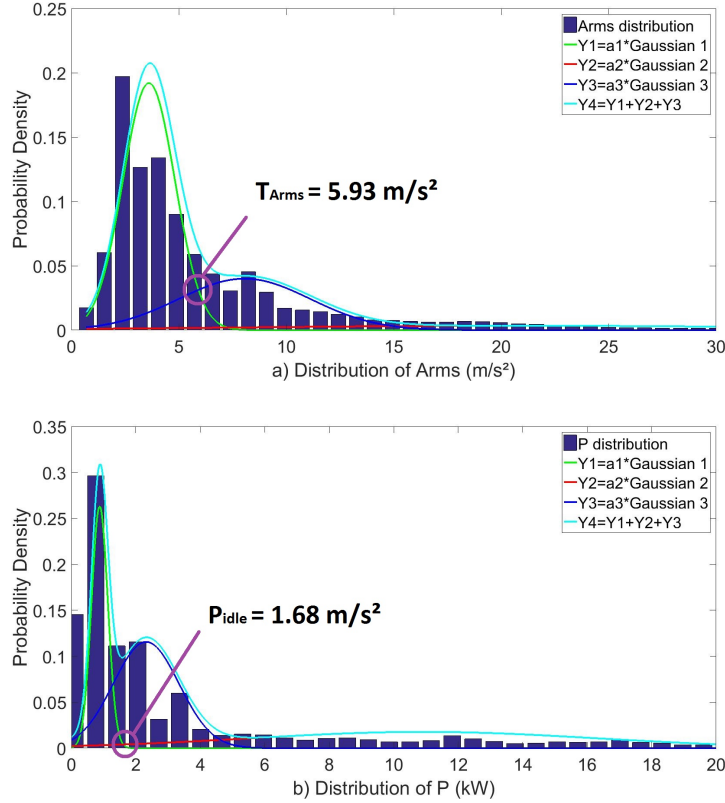


Figure 6. Distribution of Arms and P (when N constant and $V_f > 0$) modeled by GMM for machine-tool #3

The distribution of Y4 (in cyan) is the sum of these 3 Gaussians ($Y4=Y1+Y2+Y3$) as shown in Fig. 6(a). The threshold T_{Arms} is defined as the intersection between the Gaussians Y1 and Y3, in order to minimize classification errors (false positives and negatives). The threshold is identified: $T_{Arms} = 5.93 \text{ m/s}^2$ is obtained.

Applying the same method, P is modeled by 3 Gaussians:

- one Gaussian represents the class *tool not cutting* (Y1 green),
- another represents the class *tool cutting with low material removal* (Y3 blue),
- the 3rd Gaussian (Y2 red) models the class *tool cutting with high material removal*.

The distribution of Y4 (cyan) is the sum of these 3 Gaussians ($Y4=Y1+Y2+Y3$), as shown in Fig. 6(b). The threshold is chosen at the intersection between the Gaussian *tool is not cutting* and the other Gaussian *tool cutting with high material removal*, thus obtaining $P_{idle} = 1.68 \text{ kW}$.

A combination of the two sensors measurements is performed. Thus, for data where *spindle is rotating at constant speed* and *axes are moving* ($V_f > 0$) see Table 1, if $Arms > T_{Arms}$ or $P > P_{idle}$, the data is assigned to the class *tool cutting*.

Fig. 7 presents data from machine-tool #3 as well as the result of the classification. The *tool not cutting* class is represented by black "+" signs on the P power curve,

the *tool cutting* class is presented by red and blue dots. The *tool cutting* class can be classified into two sub-classes: *tool cutting with constant engagement* (in red points) and *tool cutting with varying engagement* (in blue points) by classification on ΔP (see Table 1). When the spindle has reached its target speed ($N=11250$ rpm in Fig. 7), the tool does not cut immediately. There is a subclass called *spindle startup*. This class is represented by green "+". It is defined by the following rule: from the reach of the target speed N until the power exceeds the no-load power P_{idle} (which represents the beginning of machining). Identify this state permits to eliminate parasitic vibrations related to lubrication spindle startup, which would otherwise lead to classification errors. The subclass *spindle startup* is also assigned to the cluster *tool not cutting*.

Cyan line represents Vf , blue line N , pink line $Arms$. The tool engagement is correctly detected.

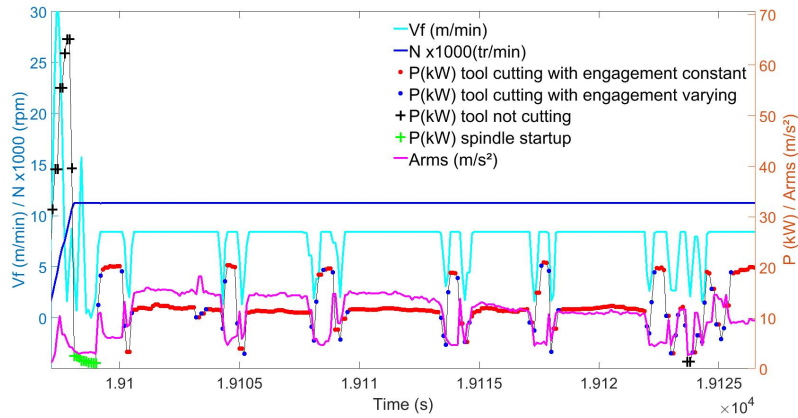


Figure 7. Classifications of material removal for machine-tool #3

5.2. Modeling and classification for machine-tool #2

The $Arms$ distribution is modeled by 3 Gaussians (see section 4):

- a Gaussian represents the class *tool not cutting* (Y1 green),
- another the class *tool cutting* (Y3 blue),
- the 3rd Gaussian represents 'severe machining vibrations' (Y2 red).

The distribution of Y4 (in cyan) is the sum of these 3 Gaussians ($Y4=Y1+Y2+Y3$) as shown in Fig. 8(a). The threshold T_{Arms} is defined as the intersection between the Gaussians Y1 and Y3, in order to minimize classification errors (false positives and negatives). This enables to identify $T_{Arms} = 5.43 \text{ m/s}^2$ for the machine-tool #2.

Applying the same method, P is modeled by 3 Gaussians:

- one Gaussian represents the class *tool not cutting* (Y1 green),
- another represents the class *tool cutting with low material removal* (Y3 blue),
- the 3rd Gaussian (Y2 red) models the class *tool cutting with high material removal*.

The distribution of Y4 (cyan) is the sum of these 3 Gaussians ($Y4=Y1+Y2+Y3$), as shown in Fig. 8(b). The threshold is chosen at the intersection between the Gaussian *tool is not cutting* and the other Gaussian *tool cutting with high material removal*. This leads to $P_{idle} = 2.57 \text{ kW}$.

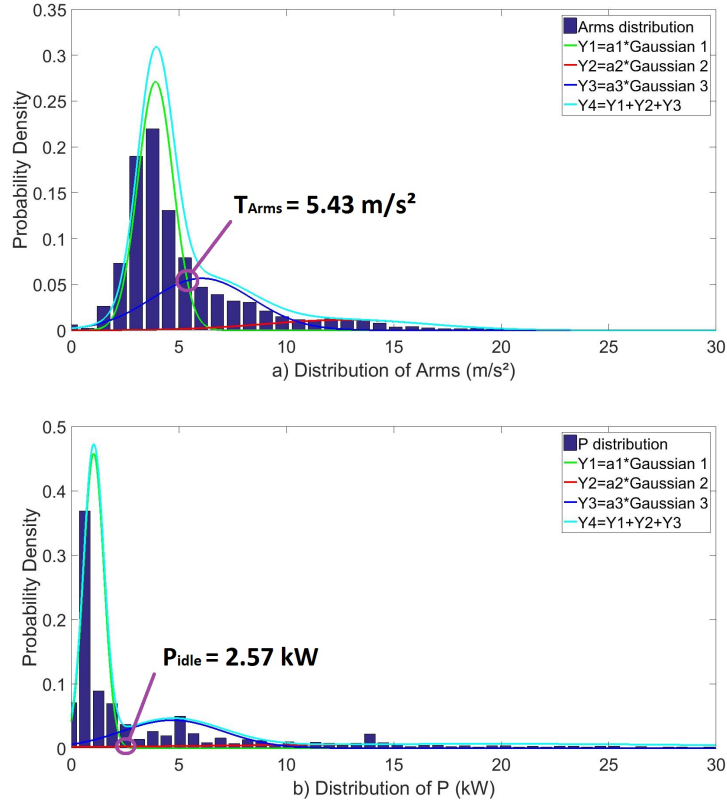


Figure 8. Distribution of Arms and P (when N constant and $V_f > 0$) modeled by GMM for machine-tool #2

In summary, three classes of the tool engagement are defined.

- *tool cutting* when $Arms > T_{Arms}$ or $P > P_{idle}$; it consists of two subclasses : *tool cutting with constant engagement* and *tool cutting with varying engagement*;
- *the tool not cutting* when $Arms \leq T_{Arms}$ and $P \leq P_{idle}$ by including the subclass *spindle startup*.

Fig. 9 plots the N (rpm), V_f (m/min), $Arms$ (m/s²) and P (kW) as well as the classification results in classes (dots and + sign) for machine-tool #2. The material removal is well classified.

6. Method validation

The estimation of the quality of the classification by machine learning is essential to choose an optimal descriptor or combining descriptors for a given data set (Wolpert 1992). Two criteria constitute the quality: accuracy and sensitivity.

6.1. Accuracy

To estimate the accuracy of the classification by GMM, manual data mining was used. In our approach, the classifications based on GMM model conduct to the predicted classes (*tool cutting* or *tool not cutting*). The actual classes correspond to 100% true classes that were constituted by manual data mining. The main steps are as follows:

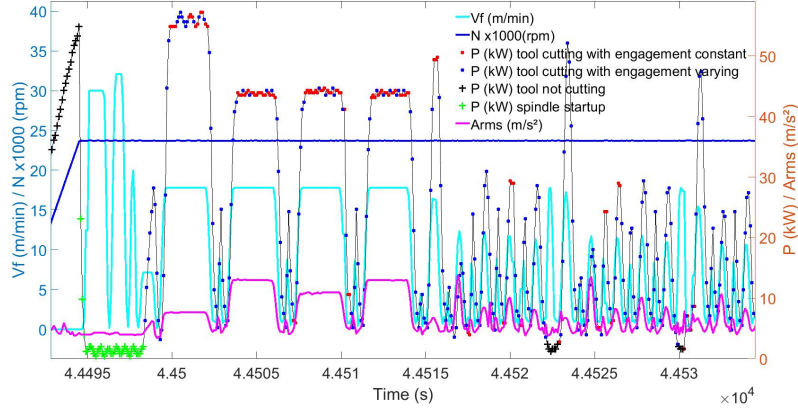


Figure 9. Classifications of material removal for machine-tool #2

- Apply GMM for training on a one-day data and identify the thresholds of T_{Arms} and P_{idle} ;
- Choose a data period and use the two thresholds to the set to predict classes: *tool cutting* and *tool not cutting*;
- Go through manual data mining, one point by one point, to obtain the actual classes;
- Compare the predicted with the actual classes and calculate the confusion matrix.

Table 2 reports the confusion matrix for 4 hours on the machine-tool #3 and Table 3 the confusion matrix for the machine-tool #2 .

Table 2. Confusion matrix for 4 hours data from the machine-tool #3

Confusion Matrix		Actual Classes	
		Tool Cutting	Tool Not Cutting
Predicted Classes	Tool Cutting	TP=51 476	FP=18
	Tool Not Cutting	FN=67	TN=92 470

Table 3. Confusion matrix for 4 hours data from the machine-tool #2

Confusion Matrix		Actual Classes	
		Tool Cutting	Tool Not Cutting
Predicted Classes	Tool Cutting	TP=60 626	FP=292
	Tool Not Cutting	FN=938	TN=93 707

Accuracy of the Classification (ACC) is the ratio of correct predictions and is computed as follows: $ACC = \frac{TP+TN}{TP+TN+FP+FN}$

The accuracy is obtained for the machine-tool #3: $ACC_{\#3}$ (4h)=99.94%, as well as for the machine-tool #2 is: $ACC_{\#2}$ (4h)=99.21%. The classifications obtained using GMM method are very accurate.

6.2. Sensitivity of the method

In order to test whether the method is sensitive to the training data set , the cross-validation method can be used. Kohavi et al. (1995) present different cross-validation methods like 'Holdout', 'Leave-one-out', 'k-fold' and 'Stratification'. In this paper, the cross-validation method 'k-fold' is used. The original sample is divided into k

samples, then one of the k samples is selected as the training set and the $(k - 1)$ other samples will constitute the validation set. The performance score is calculated. The operation is repeated k times so that each sub-sample is used once as a training set. The average of the performance scores is finally calculated to estimate the accuracy of the classifications. Here 10 days were chosen ($k=10$) as the original sample. The main steps are as follow. For each day:

- Apply GMM to the training set to obtain its thresholds of $Arms$ and P ,
- Apply these new thresholds to the validation set (nine other days) to obtain the predicted classes,
- Compare these predicted classes with the actual classes and calculate the confusion matrix. The accuracy for each days is obtained.

The thresholds of $Arms$ and P for each day in the training sets as well as corresponding accuracy when applying these thresholds to the validation set for the machine-tool # 3 and the machine-tool # 2 are respectively reported in Fig. 10(a and b). The horizontal dotted lines are the thresholds of $Arms$ and P as well as the corresponding accuracy obtained in the validation set in these two machine-tools.

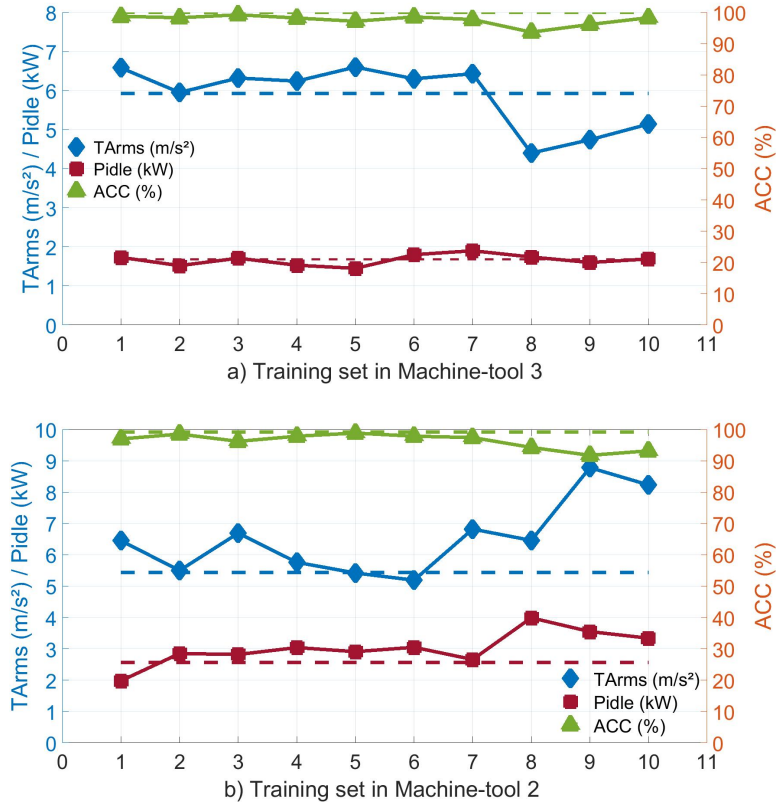


Figure 10. The new thresholds of $Arms$ and P obtained in the training sets as well as these thresholds obtained in validation sets for (a) machine-tool #3 and (b) machine-tool #2

With 10 sets, the mean accuracy of the classification for the machine-tool #3: $ACC(k\text{-fold})_{\#3} (4h)=97.60\%$, and for the machine-tool #2: $ACC(k\text{-fold})_{\#2} (4h)=96.28\%$. This shows the robustness of the proposed method. The mean accuracy is lower than the one using the same set for training and validation. It is because the thresholds for *materials removal or not* (T_{Arms} and P_{idle}) may slightly change as time

goes by, due to the variation of the machine condition (e.g. wear of the spindle).

Nevertheless, the mean accuracy obtained is high enough that the thresholds learned by GMM during one-day can be used for any other day of production on the same machine-tool.

7. Application of the contextual classifications for KPIs evaluation on production data

According to the previous validation steps, the contextual classification made by the proposed method is accurate and robust. Thus, Key Performance Indicators can be calculated based on this contextual classification. For example, it is interesting for the industry to know:

- Smart Overall Equipment Effectiveness (OEE) of the machine-tool.

Fig. 11 stresses the real machine-tool use rate during the complete spindle lifetime (215 days) for machine-tool # 2. The contextual classification enables to determine at each instant if the machine-tool is stopped (in red), removing material (cyan and yellow) or not (in pink). Then, during machining, operations dedicated to high material removal (in cyan) or low material removal (i.e. finishing operations, in yellow) can be aggregated separately (contrary to classical OEE computations). Note that the factory where data were collected works in a three-shift system 5 days a week, and that stopped times of Fig. 11 include week-end.

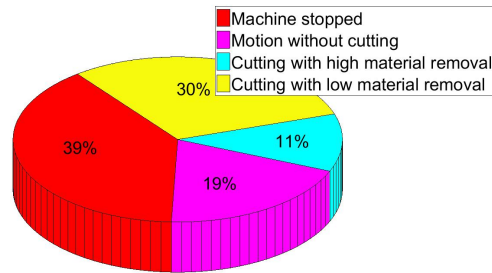


Figure 11. Machine-tool OEE during the complete spindle lifetime for the machine-tool # 2

- The programs which generate more chatter when cutting materials.
- The tools which induce more chatter when cutting materials.

For the denoising reasons, the criterion for chatter detection Godreau et al. (2019) should be evaluated only in the context where the tool is cutting. The proposed classification method is therefore applied. Fig. 12(a) shows the pie charts representing the faulty work-piece programs in terms of chatter for the complete spindle lifetime of machine-tool # 2. Fig. 12(b) shows the pie charts representing the chatter occurrences ratio per tool for the complete spindle lifetime of machine-tool # 2, which is also evaluated in the context where the tool is cutting.

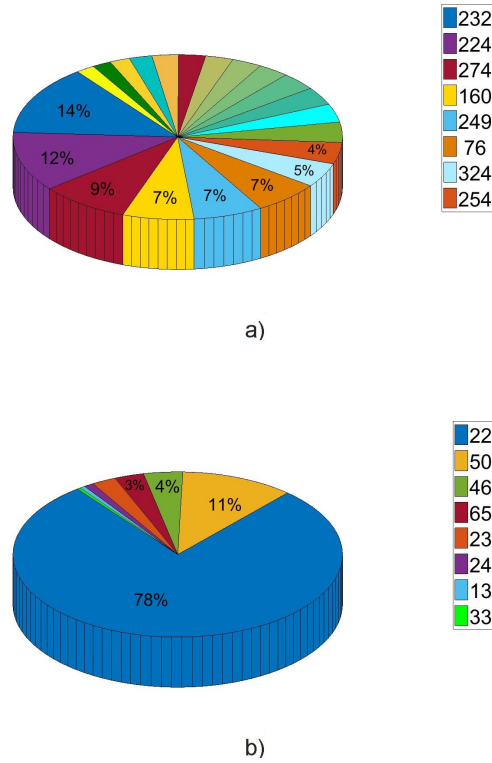


Figure 12. Pie charts representing the chatter occurrences per workpiece program (a) and per tool (b) during the complete spindle lifetime for machine-tool # 2

8. Conclusion

This paper proposes an original contextual classification of data for smart machining based on unsupervised machine learning by Gaussian mixture model. The following generic contributions were obtained:

- (1) Complete business rules for contextual classification,
- (2) A methodology, based on GMM and BIC, to determine the different states of the machine-tool,

Those proposition were validated on the raw data used in this paper was collected and stored by the device Emmatools which is installed on four machine-tools in two factories producing aeronautical structural parts.

- A classification of the *tool cutting or not*, by combining GMM thresholds of vibration measurements $Arms$ and power measurements P , was validated on 2 different machine-tools.
- k-fold validation enables to conclude that the thresholds learned by GMM during one-day can be applied to any other days for the same machine-tool. It was also found that the thresholds learned by GMM during one-day data may slightly change due to the variation of the machine condition.
- this contextual classification permit to obtained precisel KPIs that facilitate decision making.

The learned values of thresholds given in this paper are specific to a given machine-tool, but the proposed machine learning methodology is replicable to any machine-tool.

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