Obsolescence Prediction based on Joint Feature Selection and Machine Learning Techniques

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Abstract: Obsolescence is a serious phenomenon that affects all systems. To reduce its impacts, a well-structured management method is essential. In the field of obsolescence management, there is a great need for a method to predict the occurrence of obsolescence. This article reviews obsolescence forecasting methodologies and presents an obsolescence prediction methodology based on machine learning. The model developed is based on joint a machine learning (ML) technique and feature selection. A feature selection method is applied to reduce the number of inputs used to train the ML technique. A comparative study of the different methods of feature selection is established in order to find the best in terms of precision. The proposed method is tested by simulation on models of mobile phones. Consequently, the use of features selection method in conjunction with ML algorithm surpasses the use of ML algorithm alone.

1 INTRODUCTION

Obsolescence is a problem that affects all sectors. It is not a new phenomenon; since the early 1990s, the rate of component obsolescence has increased rapidly. This is particularly well illustrated by electronic components, especially for smartphones. Smartphones are the devices most subject to rapid renewal due to their obsolescence, whether technical, software or aesthetic. For example, when manufacturers still offer new versions or updates that are incompatible with previous models, we talk about software and aesthetic obsolescence. But when battery usage is reduced due to a small number of cycles or when repair becomes increasingly complicated (with models that are almost impossible to disassemble and spare parts unavailable), we speak of technical obsolescence.

Indeed, obsolescence is inevitable but anticipation and careful planning can minimize its impact and potentially high cost. The aim of obsolescence management is to ensure that obsolescence is managed as an integral part of design, development, production and maintenance in order to minimize costs and negative impact throughout the product life cycle (Group, 2016). Thus, the purpose of obsolescence management is to determine: the optimal dates and quantity of last time to buy (LTB), the optimal date for redesign, the components that should be considered for redesign or that should be replaced (Meng et al., 2014).

Sandborn has defined three terms for obsolescence management as follows (Sandborn, 2013):

- Reactive management consists in taking actions when the obsolescence has already occurred.
- Proactive management is implemented for critical components that have a risk of going obsolete.
- Strategic management is done in addition to proactive and reactive management and involves the determination of the optimum mix of mitigation approaches and design refreshes.

The most common type of management used is reactive management because it is easier to implement. It is advisable to use it only if the cost associated with the obsolescence of a component is low (Pingle, 2015). However, if the probability of obsolescence and associated costs are high, it is recommended to apply proactive management strategies to minimize the risk of obsolescence and associated costs (Rojo et al., 2010). In fact, forecasting the occurrence of obsolescence is the key factor in proactive management (Sandborn et al., 2011). For this reason, many

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researchers have focused on the development of methods based on the prediction of obsolescence (Solomon et al., 2000; Ma and Kim, 2017; Sandborn, 2017; Trabelsi et al., 2020).

Recently, with the emergence of machine learning techniques, some works have been published presenting methods based on machine learning for the prediction of obsolescence (Jennings et al., 2016; Grichi et al., 2017). In these researches, the authors mainly used the random forest algorithm to predict the state (obsolete or available) of the product. In the same line, this work highlights the value of the ML techniques to improve the quality of the obsolescence prediction. In fact, the obsolescence depends on the features of the product, but not all the features have the same effect. For this, a feature selection method must be used before processing the prediction approach in aim to select the most important and significant features. In this case, the following challenges must be overcome:

- What are the main algorithms that are best adapted to select the most important features?
- How does the feature selection method improve the obsolescence prediction model?

The remain of this paper is organized as follow: Section 2 presents the related works on forecasting techniques. In section 3, we present the proposed machine learning-based methodology and the feature selection procedure used to obsolescence prediction. Therefore an explanation of the case study and results are presented in section 4. Finally, some conclusions and future work are given in section 5.

2 RELATED WORKS

This section presents an overview of the obsolescence concept in the first part. Then, we present the problem of feature selection and different methods used for supervised learning. Supervised learning is where the computer is equipped with sample inputs that are labeled with the desired outputs (Brownlee, 2016).

2.1 Obsolescence Concept

According to IEC 62402, obsolescence is "the transition of an item from available to unavailable from the manufacturer in accordance with the original specification". Several factors are responsible for product obsolescence, including technological evolution or innovation, government-imposed laws and regulations, market demand, etc.(Bartels et al., 2012). Obsolescence is considered as a change that may affect the product. It can be considered as voluntary or involuntary. When the change is made by the manufacturer itself to promote new products, increase market share and sales (Déméné and Marchand, 2015), or when the customers decide to stop using the product for reasons, such as economics (for example, when the cost of maintenance is higher than the purchase of a new one), or aesthetics, obsolescence is considered voluntary. While, when the change made to the product is independent of the customer or manufacturer, such as government imposed regulations, the obsolescence is considered involuntary, (Bartels et al., 2012). In the scientific literature (Bartels et al., 2012; Sandborn, 2007; Mellal, 2020), several obsolescence typologies have been identified, including the following:

- **Technological Obsolescence:** occurs when there is a new technology that can replace the old one.
- **Functional Obsolescence:** is related to a technical defect that makes the product unusable.
- **Aesthetic Obsolescence:** is related to fashion effects and consumer psychology.
- **Logistical Obsolescence:** means that the product is no longer procurable due to diminishing manufacturing sources and material shortages.
- **Economic Obsolescence:** is related to the high cost of using, repairing and/or maintaining the product.

The obsolescence process ideally goes through different phases. The manufacturer announces the end of life of the product (Product Discontinued Notification) and sets a date by which the officially obsolete product will no longer be sold (Last Time Buy). During the intermediate phase (Phase Out), customers can still stock up and build up a stock of the obsolete product. The increasing rate of obsolescence leads to several risks. In (Mellal, 2020), the author discussed the various risks causing by the obsolescence in different sectors.

To reduce the affects of obsolescence, many researchers have already worked on forecasting obsolescence. The existing methods can be classified into two categories: mathematical-based approaches and machine learning-based approaches. In this paper, we will focus on the ML-based approach developed by (Jennings et al., 2016). The authors are presented a ML-based method to predict the status (Available/ Discontinued) of the product. A comparative study of ML techniques was also developed in this work. The dataset used to illustrate this approach contains information about the launch date, some technical features (chosen by the authors), and the status of the smartphone. As discussed above, product obsolescence depends on the most relevant features. Therefore, one of the important points is to determine the most relevant features for the classification of these products.

2.2 Feature Selection

The problem of feature selection has become increasingly important in the field of data analysis and machine learning (Samb et al., 2012). The feature selection is a technique that selects among original features a subset of the most important and significant attributes. In the context of supervised learning, this subset should allow meeting the target purpose, namely the accuracy of learning, the speed of learning, or the applicability of the proposed model (Khalid et al., 2014). According to (Babiker et al., 2019), the feature selection methods can be divided in three main categories: Filter, Wrapper, and Embedded method:

1. **Wrapper Method:** evaluates a subset of features by its classification performance using a learning algorithm (Kohavi et al., 1997). The learning algorithm works on the totality of instances with different subsets of features. It provides for each of them the estimated precision of the classification of the new instances. The subset inducing the most accurate classifier is selected. The complexity of the learning algorithm makes the wrapper method very expensive in terms of time where it becomes impractical when the number of initial features is large.
2. **Filter Method:** is a pre-processing method that is done before the learning process and independently of any machine learning algorithms. Instead, the relevance of the feature to the outcome variable is determined based on the feature's score in various statistical tests. Compared to wrapper methods, filter methods are much faster because they do not involve training the models.
3. **Embedded Method:** is performed by a specific learning algorithm that performs feature selection during the training process. It differs from other methods in the way feature selection and learning interact.

Figure 1 illustrates these three categories of feature selection.

In this paper, a comparative study will be done to choose the best algorithm for feature selection of Filter, Wrapper, and Embedded types. To make the comparison feasible, we propose to identify the subset of features selected by automatic methods and then using it as the training data for the predictive model. In section 3, we define precisely the steps of the used method.

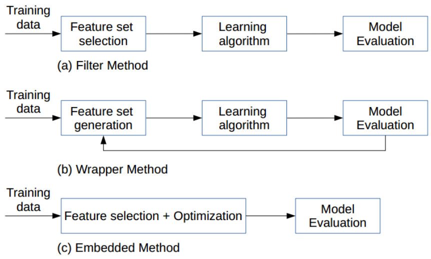

Figure 1: Comparison between (a) filter method, (b) wrapper method, and (c) embedded method for feature selection (Lee, 2009).

3 PROPOSED APPROACH

More and more companies have large amounts of data that are valuable resources for obsolescence management. However, as these resources cannot be sufficiently analyzed and evaluated, they are worthless for the company. To overcome this problem, machine learning techniques are being developed. Some researchers have focused on the application of ML techniques for the prediction and detection of obsolescence (Jennings et al., 2016; Grichi et al., 2017). To update the approach proposed by (Jennings et al., 2016), in this work we propose an obsolescence prediction based on joint feature selection and ML Technique.

As shown in Figure 2, the first step is to collect the data to identify the product's obsolescence. The collected data must contain information about technical specifications, launch date, production end date, and all other data may affect the product obsolescence. To obtain more accurate forecast results, the strengths of the feature selection method and the prediction model will be unified. Therefore, a crucial step concerning the feature selection will have to be done before starting the prediction model. At this stage, a subset of the most relevant features is selected. The third step is to choose a predictive model among supervised learning techniques. The predictive model aims to predict the status (available or obsolete) of the product in the test dataset. The performance of predictive models is evaluated using the confusion matrix (Zemouri et al., 2018). This matrix contains a summary of the number of correct and incorrect predictions allowing to quantify errors made. In our case, the confusion matrix is shown in Table 1.

Based on this information, three metrics are calculated:

1. Accuracy: it generally indicates how "right" predictions are. It is calculated as follow:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \qquad (1)$$

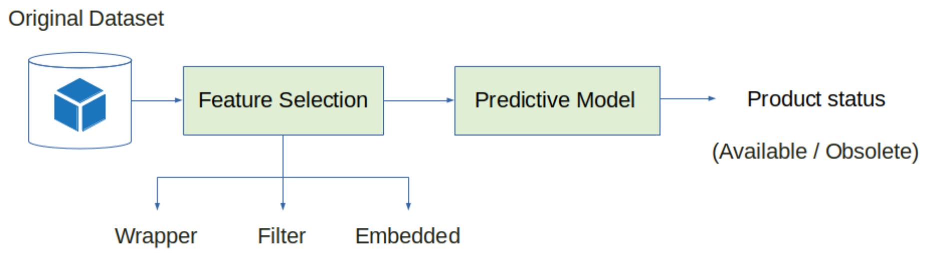

Figure 2: The proposed approach.

Table 1: The confusion matrix.

		Predicted class	
		Obsolete	Available
Actual class	Obsolete	True Positive (TP)	False Negative (FN)
	Available	False Positive (FP)	True Negative (TN)

1. Precision: it measures the class agreement of the data labels with the positive labels given by the classifier.

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

2. Sensitivity or true positive rate (TPR): it measures how often the model chooses the positive class when the observation is in fact in the positive class.

$$TPR = \frac{TP}{TP+FN} \tag{3}$$

These metrics are calculated for different ML-techniques to compare them and choose the best one.

4 CASE STUDY

The case study will demonstrate the utility of the feature selection method in the predictive model. The smartphone market is evolving very fast, driven by the regular introduction of new technologies and serious competitors, and by fashion effects. Therefore, smartphones are used as the illustrative case of the proposed approach.

4.1 The Dataset

The database contains specific information on several smartphone models and whether their status is available or discontinued. There are more than 59 features such as digital mobile phone technology, battery capacity, smartphone dimensions, display characteristics, operation system, etc. The data was collected on one of the most popular mobile phone forums (GSM Arena) [1]. Figure 3 shows an example of iPhone 6 Plus specifications.

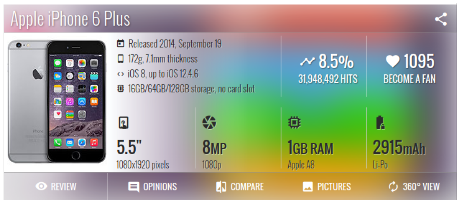

Figure 3: Example of technical specification from GSM-Arena.

According to estimates by Canalys [2], the global smartphone market was mainly divided between the Apple, Samsung, Huawei, Xiaomi and Oppo brands. Therefore, the number of instances is reduced to 1257 models of the 5 brands divided into 576 available smartphones and 681 as discontinued (or obsolete).

As is well known in the machine learning community, reducing input variables is a useful operation. It has a great impact on the computer's time and accuracy. Therefore, there is a great need to apply an algorithm to select among these most relevant features.

The data present in the site can miss values and even have erroneous information. These gaps reflect the limitations imposed by some industries to have a complete database. To remedy this problem, the data must first be prepared.

The dataset has been formatted in a machine learning compatible format. To handle missing data, the mean imputation method is used. Once the data is formatted, feature selection methods is applied. The first part of this case study is to compare the different methods of feature selection. To this end, we have used several feature selection algorithms for the three methods.

[1]https://www.gsmarena.com
[2]https://www.canalys.com/newsroom/canalys-global-smartphone-market-q4-2019

4.2 Used Tools

In this section, the used techniques for feature selection and for machine learning are presented. For supervised learning the most used techniques are:

- **Random Forest (RF):** is a meta-estimator that applies many decision tree models to different subsamples of the data set and the end result is obtained as an average of these models, see (Grichi et al., 2017). The averaging process avoids overfitting and therefore improves the accuracy of the classification.
- **Artificial Neural Network (ANN):** is a supervised machine learning tool that can learn a non-linear function. It can be used for classification or regression which make it one of the most used fault detection technique (Zemouri et al., 2019).
- **Support Vector Machine (SVM):** aims to find a separating hyperplane that separates the different classes. To do this, the Optimal Separating Hyperplane (OSH) is defined as the hyperplane situated between the classes that maximize the margin between them (Wang et al., 2012).
- **K-Nearest Neighbors (KNN):** The nearest neighbors approach is based on finding a fixed number k of samples from a training dataset, which are the closest ones, in terms of distance, to the new instance to predict its label, (Omri et al., 2020).
- **Naive Bayes (NB):** The Naive Bayes (NB) method is a simple, probabilistic, and supervised classifier, see (Rish et al., 2001). This technique is based on coupling the *Bayes theorem* with the *Naive* hypothesis of conditional independence between every pair of features given the value of the class variable.

The used feature selection algorithms in this case study are presented as follow. For filter method, we used:

- Correlation-based Feature Subset Selection is an algorithm that evaluates the importance of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them (Li et al., 2011).
- Variance Threshold is a simple baseline algorithm to feature selection. According to (Zhao et al., 2013), it aims to remove the features whose variance does not meet some threshold. It automatically removes all features with zero variance, i.e. features that have the same value in all samples.

For wrapper method we used:

- Wrapper attribute subset evaluator designed to evaluate features subsets by using a learning technique. It uses cross validation for estimating the precision of the learning technique used (Gutlein et al., 2009).
- Backward Feature Elimination is a feature selection technique while building a machine learning model that used to remove features without significant effect on the prediction of output (Kostrzewa and Brzeski, 2017).

For embedded method we used:

- Ridge regularization is a process that consider all the features into the model and try to regularize the coefficient estimates of a feature such that a large number of coefficient estimates shrink towards zero (Cawley, 2008).
- Lasso allows to select a restricted subset of features by shrinking some of the coefficients to zero, that means that a certain features will be multiplied by zero to estimate the target (Muthukrishnan and Rohini, 2016).

The different simulations of feature selection and classification with machine learning were done using Python libraries.

4.3 Results and Discussion

Here in all the instances, we have the target which takes 0 or 1 respectively when the smartphone is obsolete the output is 0, if it is available the output is 1. Table 2, represents the precision and the sensitivity of the classification algorithms for different feature selection techniques. A cross validation has been performed with k=5. This allows to evaluate the impact of the selected features on the model performance.

These results show that the Random Forest (RF) technique has better accuracy than other algorithms without the feature selection step. This accuracy is improved by applying feature selection techniques such as wrapper methods, as shown in Figure4.

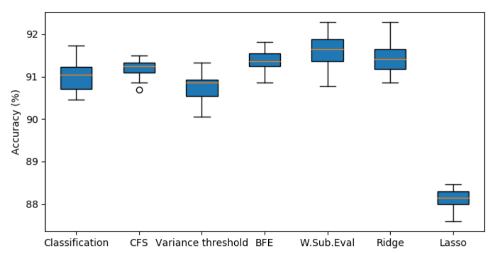

Figure 4: The comparison of the Random Forest accuracy with different feature selection techniques.

Table 2: Simulation results.

Feature selection		Performance	RF	ANN	NB	KNN	SVM
Without feature selection		**Accuracy**	**91.02±0.34**	82.39±2.5	85.20	82.26	54.18
		Precision	**93.41±0.35**	80.05±5.48	81.69	86.35	54.18
		Sensitivity	89.62±0.35	86.55±2.46	93.69	79.88	**100.00**
Filter	**Cfs Subset Eval**	**Accuracy**	**91.19±0.2**	88.26±3.88	89.98	89.98	89.82
		Precision	93.83±0.16	90.03±3.69	93.29	92.50	**94.38**
		Sensitivity	**89.62±0.35**	88.34±7.13	87.81	88.69	86.34
	Variance Threshold	**Accuracy**	**90.77±0.3**	80.78±2.96	80.35	82.18	55.93
		Precision	**93.24±0.24**	84.67±3.07	75.23	84.05	55.37
		Sensitivity	89.44±0.51	79.02±6.25	95.01	82.82	**96.18**
Wrapper	**Backward Feature Elimination**	**Accuracy**	**91.36±0.23**	88.88±0.77	89.02	82.74	91.09
		Precision	93.38±0.33	90.35±1.07	88.95	85.91	**94.52**
		Sensitivity	90.47±0.34	89±1.12	**91.04**	81.50	88.69
	Wrapper subset eval	**Accuracy**	**91.62±0.37**	84.17±3.07	62.21	84.17	54.26
		Precision	**93.65±0.23**	85.8±2.43	58.97	87.77	54.24
		Sensitivity	90.69±0.6	84.94±6.5	99.41	82.23	**99.56**
Embedded	**Ridge**	**Accuracy**	91.43±0.35	81.63±5.76	80.90	**91.65**	91.49
		Precision	93.91±0.14	85.94±7.59	76.53	**94.44**	94.29
		Sensitivity	90.02±0.62	80.23±10.82	**93.39**	89.87	89.72
	Lasso	**Accuracy**	**88.1±0.22**	82.42±2.68	86.48	82.26	54.18
		Precision	**88.86±0.29**	87.31±2.43	81.43	86.35	54.18
		Sensitivity	89.22±0.23	79.15±5.5	97.21	79.88	**100.00**

Moreover, for the predictive model SVM, the application of the ridge technique improved its accuracy up to 91.49%. Whereas without feature selection technique it has sensitivity 100% that means that the SVM only can not identify the available smartphone, it considers that all the smartphones were obsolete. Therefore, it is more important to use feature selection methods and ML algorithms than to use only ML algorithms. As shown in Table 2, obsolescence prediction based on backward feature elimination and ANN Technique is more accurate than using ANN only. As mentioned above, feature selection technique allows to select only those features which are necessary.

Comparing all algorithms of feature selection, we note that backward feature elimination seems to be the best technique to increase the performance of the predictive model. Figure 5 shows the improvement of the accuracy of the different ML-techniques using the backward feature elimination.

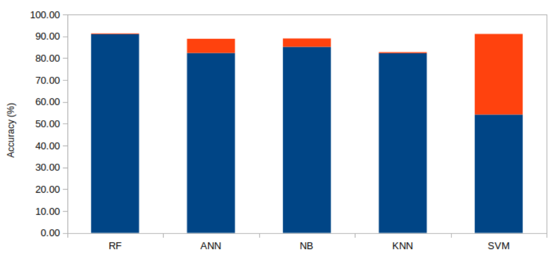

Figure 5: The improvement of the accuracy en applying Backward Feature Elimination.

As shown in the Table 3, we can see that through the application of the feature selection technique, the number of features used to train the predictive model has been reduced from 59 to 21 maximum. Therefore, the feature selection technique allows to optimize the training time and reduce data collection effort.

Table 3: The number of features selected by the different feature selection techniques.

Feature selection techniques		Features number
Filter	CfsSubsetEval	7
	VarianceThreshold	16
Wrapper	Backward Feature Elimination + RF	10
	Wrapper subset eval + RF	14
	Backward Feature Elimination + ANN	10
	Wrapper subset eval + ANN	20
	Backward Feature Elimination + KNN	10
	Wrapper subset eval +KNN	10
	Backward Feature Elimination + NB	10
	Wrapper subset eval + NB	7
	Backward Feature Elimination + SVM	10
	Wrapper subset eval + SVM	21
Embedded	Ridge	13
	Lasso	16

The figure 6 illustrates the features selected by the different techniques. The most relevant feature, which is selected by 11 techniques, corresponds to the launch date of the smartphone.

From this study, it is proven that there is a small set of features that impact the smartphone obsolescence. Thus, an efficient obsolescence prediction approach can be established by controlling these features. However, the phenomenon of obsolescence is a dynamic concept which evolves over time which means that these features can be modified depending on the date of observation. Therefore, each obso-

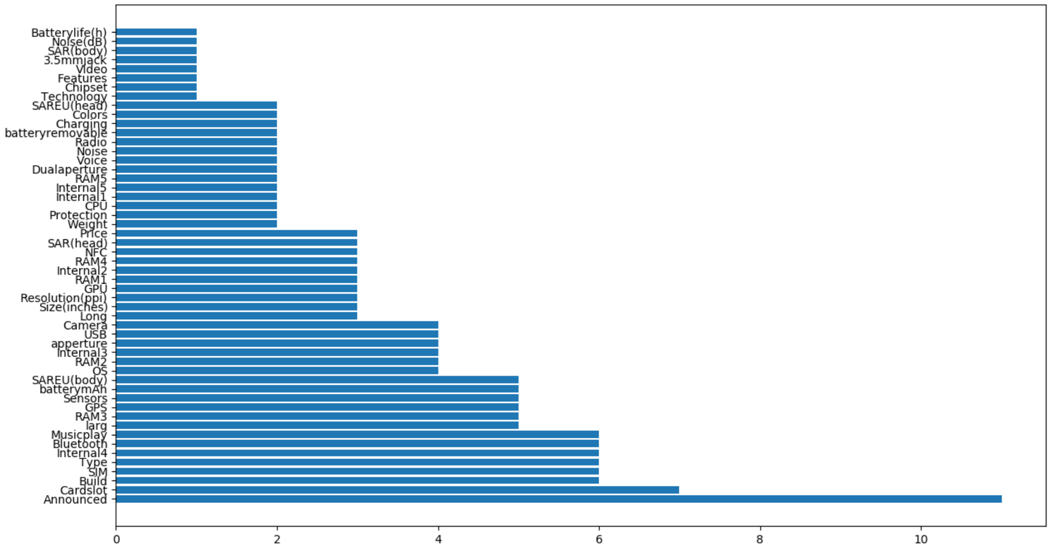

Figure 6: The most important features selected by the different feature selection techniques.

lescence prediction must be presented with a validity horizon. As a perspective for this work, we propose to study the evolution of the features that impact obsolescence for a given system.

In this paper, obsolescence status is considered as the case where the manufacturer announce the product end-of-life. However, for the user, the problem arises in other words. Indeed, he can decide for himself to abandon the use of a product that has become useless due, for example, to its replacement by a new product. In this context, an other limitation to our approach is the behavior of costumers. Obsolescence status is then modified according to this issue. Hence, it is necessary to integrate this customer-related information into the study of obsolescence by proposing an approach based on natural language processing.

5 CONCLUSIONS

In this paper, we have discussed a new joint technique of feature selection and machine learning used for obsolescence prediction. Our approach is applied in a real data set concerning the obsolescence of smartphones. The results show that the obsolescence of the smartphone is linked to specific features such as the launch date, the ability of the smartphone to insert a memory card slot,etc. Thus, an effective obsolescence prediction strategy lies in the prevention of obsolescence of these features. However, this work is limited in the obsolescence detection (binary class) without taking into account its evolution over time and its dependence on the system environment (market and entities).

To go further, the authors believe that it is necessary to evaluate obsolescence as a dynamic problem that evolves over time. Thus, the features which have an impact on the obsolescence of a system during a given period can be changed during another period. In this context, a data-driven obsolescence management approach is needed. This approach should bring together the different data that characterize the system environment (technologies, laws, aesthetics, etc) in order to control adapt the prediction model to these environment change.

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