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RESEARCH ARTICLE

Developing an SVM-based ensemble learning system for customer risk identification collaborating with customer relationship management

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Abstract In this study, we propose a support vector machine (SVM)-based ensemble learning system for customer relationship management (CRM) to help enterprise managers effectively manage customer risks from the risk aversion perspective. This system differs from the classical CRM for retaining and targeting profitable customers; the main focus of the proposed SVM-based ensemble learning system is to identify high-risk customers in CRM for avoiding possible loss. To build an effective SVM-based ensemble learning system, the effects of ensemble members' diversity, ensemble member selection and different ensemble strategies on the performance of the proposed SVM-based ensemble learning system are each investigated in a practical CRM case. Through experimental analysis, we find that the Bayesian-based SVM ensemble learning system with diverse components and *choose from space* selection strategy show the best performance over various testing samples.

Keywords support vector machines (SVM), ensemble learning, diversity strategy, selection strategy, ensemble strategy, customer relationship management (CRM)

1 Introduction

Customer relationship management (CRM) has become more and more important today, this is due to the intensive competitive environment and increasing rate of change in the customer market. Generally, CRM is defined as a dynamic process of managing a customer-enterprise relationship such that customers are retained to continue mutually beneficial commercial exchanges and are dissuaded from participating in exchanges that are unprofitable to the enterprise [1]. Usually, most enterprises are interested in knowing who will respond, activate, purchase, or use their products or services. However, customer risk avoidance and management is also a critical component in order to maintain profitability in many industries, such as commercial banking and insurance. These businesses are concerned with the amount of risk they are taking by accepting someone or a certain corporate entity as a customer. Sustainability and profitability of these businesses particularly depends on their ability to distinguish faithful customers from bad ones [2,3]. To enable these businesses to take either preventive or corrective action, it is imperative to satisfy the need for efficient and reliable model that can accurately identify high-risk customers with a potential default trend.

In such a CRM system that focuses on customer risk identification, a generic approach is to apply a classification technique on similar data of previous customers, both faithful and delinquent customers, in order to find a relationship between their characteristics and the probability of default [2,3]. One important ingredient needed to accomplish this goal is an accurate classifier in order to

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categorize new customers or existing customers as good or bad. In the process of customer classification, data mining techniques, especially classification techniques, play a critical role.

Historically, the first approach of managing customer risk started with the use of empirical methods proposed by large American banks, such as the *three A* method, the *five C* method, and the *credit-men* method [4]. The financial ratios methodology was developed for corporate customer risk identification problem in Ref. [5]. Subsequently, many statistical models, some optimization methods and the emerging artificial intelligent (AI) techniques have been used to classify the customer risks. Details of these risk identification approaches are provided in Refs. [2–4].

Recent research has found that the unitary classification technique did not produce consistently good performance because each classification technique had its own shortcomings and was suitable in different situations [3,4]. The ensemble classification technique is an effective way to remedy this drawback. Ensemble classification is not new and some similar studies including Ref. [3] have provided some useful practices for ensemble classification. In our study, we propose a support vector machine (SVM) based ensemble learning method to identify the high risk customer to help improve CRM in enterprise. The main reasons for selecting SVM over other AI techniques, such as artificial neural networks (ANN), lie in the following distinct advantages of SVM. First of all, SVM requires fewer prior assumptions about the input data. Second, they can perform a nonlinear mapping from an original input space into a high dimensional feature space, in which they construct a linear discriminant function to replace the nonlinear function in the original input space. This characteristic also solves the dimensionality problem, which is a problem caused by the exponential increase in volume associated with adding extra dimensions to a mathematical space, because its computational complexity is independent of the sample dimension. Third, they attempt to learn the separating hyperplane to maximize the classification margin. These important traits make SVM popular in many applications. We put particular emphasis on investigating the effects of ensemble members' diversity, ensemble member selection, and ensemble strategy on performance of the proposed ensemble learning system in CRM.

In Section 2, a five-stage SVM ensemble learning procedure for CRM is proposed to identify high risk customer in details. In Section 3, we conduct some experiments with a real-world customer data set, and particularly the impacts of ensemble members' diversity, ensemble member selection, and ensemble strategy on performance of ensemble data mining system are investigated. Finally, some conclusions are drawn in Section 4.

2 SVM-based ensemble learning process for CRM

As noted earlier, integrating multiple classification models into an aggregated output has been an effective way to improve the classification performance [3]. A definition of effective ensemble classifiers was introduced by Hansen and Salamon [6], who stated: "A necessary and sufficient condition for an ensemble of classifiers to be more accurate than any of its individual members is if the classifiers are accurate and diverse." An accurate classifier is the one that is well trained and whose error rate is better than a random selection of output classes. Two classifiers are diverse if they make different errors on the same input values. Our method uses SVM which is a more robust model than the ANN based method presented in Ref. [6]. Fig. 1 illustrates a general procedure of the SVM-based ensemble learning system, which is built from typical CRM processes.

In Fig. 1, we can see the five stages for building an SVM-based ensemble learning system: data preparation, individual classifier construction, ensemble member selection, ensemble classifier construction, and model evaluation, which are described in the following subsections.

2.1 Stage I: data preparation

The first step of this ensemble data mining system is to prepare input data into a readily usable format. The main task of this phase is to collect related data and perform the necessary data preprocessing. Typically, some variable selection methods, such as sequential search, nonlinear optimization [7] and genetic algorithms (GA) [8], and subsequently data sampling techniques should be performed now for convenience later. A systematic research piece on data preparation for complex data analysis is performed by Yu et al. [8]. In the CRM system, the effects of variable selection and data sampling on performance of predictive models have been studied in detail by Kim [9] and thus these will not be emphasized here.

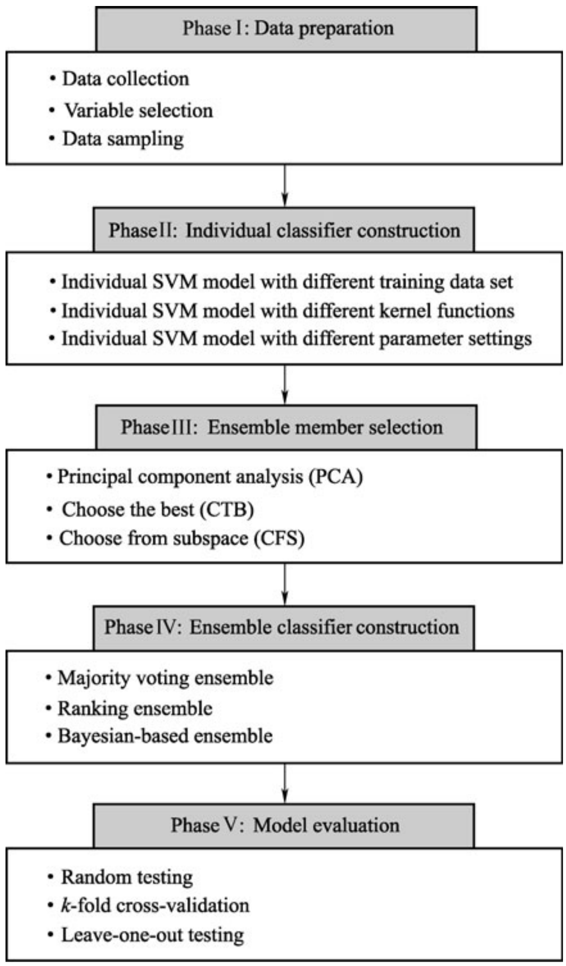

Fig. 1 General procedure of SVM-based ensemble learning system

2.2 Stage II: individual classifier construction

According to the bias-variance-complexity trade-off principle [10], an ensemble learning system consisting of diverse individual learning models, i.e. base models, with much disagreement is more likely to perform well. Therefore, it is important to discover how to generate a diverse model as this is the key to the construction of an effective ensemble model [4]. There are three main ways of generating diverse base models for the SVM classifier.

(a) Utilizing different training data sets. This is done by data sampling presented in the first stage.

(b) Changing the kernel functions. In SVM modeling, polynomial functions and Gaussian functions are used as kernel functions.. Usually a function that satisfies the Mercer condition can be used as kernel function of SVM model.

(c) Varying the SVM model parameters. In SVM modeling, margin parameter C and kernel parameter σ^2 when Gaussian kernel function is selected, and order number d if polynomial function is chosen, are used.

Although there are many ways to create diverse base models, the above approaches are not necessarily independent. In many situations, they are employed together in one ensemble learning system. A common method to create an SVM-based ensemble learning system is to train a group of SVM base models with different parameters and then use a selection criterion, e.g. diversity and accuracy, to pick out some of them, and construct an ensemble classifier with these candidate SVM base models.

2.3 Stage III: ensemble member selection

After training, each member in the ensemble learning system can generate its own result. If the individual members of the ensemble learning system are diverse, disagreeing results for the same inputs are expected. However, not all individual base classifiers generated by the previous stage are used to create an ensemble learning system. On the contrary, we need select those most diverse classifiers for ensemble purpose in terms of some specified criteria. This criterion of selecting ensemble members is described in Partridge and Yates [11], where some error diversity measures used to choose diverse classifiers are introduced. In fact, ensemble member selection is a process of choosing a subset of all generated individual classifiers by eliminating some highly-dependent candidates with lower accuracy. If we can extract as much information as possible from given data whilst using the smallest number of candidate models, it is possible to make a great saving in computational cost. There are many algorithms, such as principal component analysis (PCA) [12], choose the best (CTB) [11] and choose from subspace (CFS) [11], for ensemble member selection. PCA is used to select a subset of members from candidate members using the maximal eigenvalue of the error matrix. The idea of CTB is to select the classifier with the best accuracy from candidate members to formulate a subset of all members. The CFS is based on the idea that for each model type, it chooses the model exhibiting the best performance. It should be noted that the term *subspace* refers to the subset of SVM models for a given SVM type, such as standard SVM proposed by Vapnik [13] and least squares SVM (LSSVM) model [14].

2.4 Stage IV: ensemble classifier construction

Whatever methods are used to create ensemble members, the definite stage of ensemble classifier construction is the integration of ensemble members. Majority voting based ensemble strategy [6], Bayesian-based ensemble strategy [15] and Dempster-Shafter based ensemble strategy [15] are the most popular methods for constructing an accurate ensemble model.

Majority voting based ensemble strategy [6] is the most popular ensemble strategy for classification problems because of its simple implementation. Ensemble members vote to decide the result the ensemble will agree upon for it to be accepted as the final output of the ensemble (regardless of the diversity and accuracy of each classifier's generation). Majority voting ignores the fact that some classifiers that lie in a minority sometimes do produce the correct results. At the stage of integration, it ignores the existence of diversity that is the motivation for ensembles.

The Bayesian-based ensemble strategy uses Bayesian conditional probability theory to obtain the belief of ensemble members and then to fuse ensemble members using the belief measure [15]. The main shortcoming is that the prior probability is unknown in some situations.

The Dempster-Shafter based ensemble strategy uses evidence theory to obtain a belief measure of ensemble members and then integrates ensemble members into an aggregated output [15]. Although some empirical studies have shown the superiority of this strategy, the computational processes are very complex.

2.5 Stage V: model evaluation

To provide a reliable measurement for ensemble models, the model evaluation is required. Usually, we split all data into two main sets: training data set, *in-sample data set*, and testing data set, *out-of-sample data set*. The former is used to build models and the latter is used to evaluate the models. Typically, there are three methods to evaluate the quality of the models.

(1) **Random testing**. This method randomly selects testing samples from the testing set and the size of testing samples is determined randomly according to the practical need. This method is very suitable for the large-size data sets.

(2) ***k*-fold cross-validation testing**. In this method, the data set is divided into *k* non-overlapping groups. We use the first *k*-1 groups as training data to train a model and test the trained model on the *k*th group. We repeat this procedure until each of the groups is used as a testing set once. We then take the average of the performance measurements over the *k* folds. This method is suitable for medium-size data sets.

(3) **Leave-one-out testing**. This method is actually a variant of *k*-fold cross-validation testing, where *k* is equal to 1. It is suitable if a small-size data set is available.

In this study, we use *k*-fold cross-validation testing to test the reliability of the ensemble models.

3 Experimental analysis

3.1 Experiment data, data preparation and evaluation criteria

In this section a real-world credit data set is used to test the performance of the SVM-based ensemble data mining model. The data set used in this study is from the financial service company of England, obtained from accessory CD-ROM of Thomas, Edelman and Crook [16]. The data set comprises detailed information of 1225 customers, including 323 observed bad customers and 902 observed good customers. Each customer is characterized by 14 attributes:

(01) year of birth
(02) number of children
(03) number of other dependents
(04) existence of a home phone
(05) applicant's income
(06) applicant's employment status
(07) spouse's income
(08) residential status
(09) value of home
(10) mortgage balance outstanding
(11) outgoings on mortgage or rent
(12) outgoings on loans
(13) outgoings on hire purchase
(14) outgoings on credit cards

For this data set, we preprocess the experiment data in the following way:

(1) To make the number of observed bad customers similar to the observed number of good customers, we triple every observed bad customer. The main reason is to avoid the occurrence of such a situation that all selected samples are good customers. Therefore, the data set

comprises detailed information of 1871 customers, including 969 observed bad customers and 902 observed good customers.

(2) We scale the values of the numerical attributes to the range [0, 1] for avoiding the dominance effect of large data.

(3) We randomly divide the scaled data set into two parts: a training set with 800 samples, and a testing set with 1071 samples.

To measure model classification performance, three commonly used evaluation criteria: type I accuracy, type II accuracy and total accuracy [2,3], are used to measure the efficiency of classification, which is elaborated as follows.

$$\text{Type I accuracy} = \frac{\text{number of both observed bad and classified as bad}}{\text{number of observed bad}}, \tag{1}$$

$$\text{Type II accuracy} = \frac{\text{number of both observed good and classified as good}}{\text{number of observed good}}, \tag{2}$$

$$\text{Total accuracy} = \frac{\text{number of correct classification}}{\text{the size of evaluation sample}}. \tag{3}$$

As a whole we use total accuracy to report the experiment results in this study. In addition, two popular SVM algorithms, namely standard SVM algorithm [13] and LSSVM algorithm [14] are used.

3.2 Experimental design

The motivation of our experiments reflects the following two goals: (a) to study the effects of ensemble members' diversity, ensemble members' selection strategy and final ensemble strategy on the performance of the SVM-based ensemble model in the process of CRM system; and (b) to evaluate the effectiveness of the SVM-based ensemble model by comparing two typical ensemble approaches presented in this study. In view of the complexity of Dempster-Shafter based ensemble method, we use the majority voting and Bayesian ensemble strategies to fuse different SVM classifiers.

Considering the first motivation, we need to create different ensemble members. To keep diversity, ensemble members were created by the following three kinds of variations:

Variation 1: changing the parameters of Gaussian kernel function, namely margin parameter C and kernel parameter σ^2;

Variation 2: varying the training data set with k-fold cross-validation sampling;

Variation 3: Using the kernel function, namely linear kernel function, polynomial kernel function, Gaussian kernel function and two-layer neural perception function are used to create different SVM classifiers.

For simplicity, ensemble members are created by the following eight ways, here referred to as E_1, E_2,…, E_8, which are created as follows. Table 1 presents the diversity source of ensemble members of the eight SVM-based ensemble models.

Table 1 The diversity source of ensemble members of the eight SVM-based ensemble models

SVM algorithms for ensemble members		Diversity sources		
Standard SVM	LSSVM	Variation 1	Variation 2	Variation 3
E_1	E_2	√		
E_3	E_4		√	
E_5	E_6			√
E_7	E_8	√	√	√

(1) Ensemble E_1 and E_2 are created by employing variation 1. Ensemble E_1 comprises 20 standard SVM models with the same Gaussian kernel function. In their Gaussian kernel function, different values for margin parameter C and kernel parameter σ^2 are used. Usually the rational interval of the margin parameter C and kernel parameter σ^2 is between 1 and 100. Ensemble E_2 comprises 20 LSSVM models with the same kernel functions and parameters as those used in E_1.

(2) Ensemble E_3 and E_4 are created by employing variation 2. Ensemble E_3 comprises 20 standard SVM models. These standard SVM models are created by using the 20 different training sets. Ensemble E_4 comprises 20 LSSVM models. These LSSVM models are created by using the 20 different training sets.

(3) Ensemble E_5 and E_6 are created by employing variation 3. Ensemble E_5 comprises 20 standard SVM models. Four different kernel functions, namely linear kernel function, polynomial kernel function, Gaussian kernel function, and two-layer neural perception function, with their different parameters are used to create different individual SVM. Ensemble E_6 comprises 20 LSSVM

models with the same kernel functions and parameters as those used in E_5.

(4) Ensemble E_7 and E_8 are created by combining variations 1, 2 and 3. Ensemble E_7 comprises 30 standard SVM models, including 10 standard SVM models based on the Gaussian kernel function with different kernel parameters, 10 standard SVM models based on the different training sets, and 10 standard SVM models based on the different kernel functions. Ensemble E_8 comprises 30 LSSVM models, including 10 LSSVM models based on the Gaussian kernel function with different kernel parameters, 10 LSSVM models based on the different training sets, and 10 LSSVM models based on the different kernel functions.

In the phase of ensemble member selection, we compare the following three selection strategies: PCA, CTB, and CFS [11,12]. In the phase of ensemble classifier construction, we compare the following two ensemble strategies: majority voting ensemble strategy and Bayesian-based ensemble strategy, as noted earlier.

For the second experimental motivation, we compare our proposed approach with Logistic regression-based (LogR) ensemble and artificial neural network-based (ANN) ensemble. LogR ensemble and ANN ensemble are also constructed with 20 different classifiers respectively. It is worth noting that for the convenience of comparison the members of the LogR ensemble and the ANN ensemble are created based on different training sets, which are the same as the training sets for the E_3 and E_4.

In addition, we select k-fold cross validation as the evaluation method. Particularly, we set $k = 2$ for two-fold cross validation. This is a reasonable compromise considering the computational complexity of our ensemble data mining system. Furthermore, estimation from twofold cross validation is likely to be more reliable than an estimate from a common practice using a single testing set.

Table 2 Total accuracy for different ensemble models

Ensemble	Selection strategy	Ensemble strategy/%	
		Majority voting ensemble	Bayesian-based ensemble
E_1	PCA	70.75	76.36
	CTB	71.30	77.68
	CFS	77.78	79.21
E_2	PCA	75.39	87.06
	CTB	77.13	88.14
	CFS	78.96	88.68
E_3	PCA	72.50	77.68
	CTB	70.81	75.63
	CFS	72.77	78.18
E_4	PCA	74.62	86.05
	CTB	75.63	85.71
	CFS	76.54	88.87
E5	PCA	69.06	77.78
	CTB	70.11	75.79
	CFS	71.35	82.18
E_6	PCA	72.77	85.63
	CTB	74.62	85.18
	CFS	75.63	87.06
E_7	PCA	72.93	81.09
	CTB	71.24	80.23
	CFS	73.35	82.69
E_8	PCA	76.57	87.89
	CTB	75.16	90.30
	CFS	79.32	91.27
LogR	PCA	57.65	60.08
	CTB	58.63	62.29
	CFS	59.49	60.86
ANN	PCA	68.63	73.35
	CTB	69.06	71.24
	CFS	68.65	72.93

3.3 Experimental results

According to the previous experiment design, different experiments are conducted and the corresponding experimental results are reported in Table 2.

To further explore the effects of ensemble members' diversity, ensemble member selection, and final ensemble strategies on performance of the SVM ensemble data mining system, we transform the numerical data into illustrative figures. Fig. 2 shows the total accuracy of ensemble models.

From Fig. 2, we can gather information that meets the first goal of our experimental motivation; we can study the effects of ensemble members' diversity, selection strategy and final ensemble strategy on the performance of the SVM-based ensemble model in the process of CRM system:

(1) Effects of diversity of individual classifiers: The total accuracy of E_7 is higher than those of E_1, E_3 and E_5 in the most of ensembles, except when employing the 2 pairs of ensemble members' selection strategy and final ensemble strategy, namely CTB+ Majority voting, and CFS+Majority voting. The total accuracy of E_8 is higher than those of E_2, E_4 and E_6 in the most of ensembles, except when employing the pairs of ensemble members' selection strategy and final ensemble strategy, namely

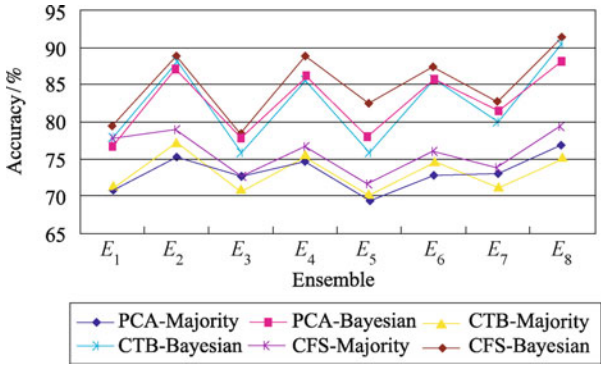

Fig. 2 Total accuracy of SVM-based ensemble models

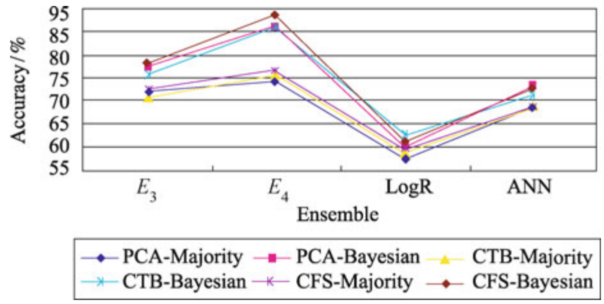

Fig. 3 Total accuracy of E_3, E_4, LogR ensemble and the ANN ensemble

CTB+Majority voting. As shown in Table 1, E_7 and E_8 employ more variations for the creations of ensemble members than E_1, E_3 and E_5, and E_2, E_4 and E_6. This indicates that more diversity of individual classifiers can improve the performance of the SVM-based ensembles models.

(2) Effects of ensemble members' selection strategy: From Fig. 2, it is clear to see that the CFS strategy always performs the best among the three strategies of ensemble members' selection whether Bayesian or majority based.

(3) Effects of final ensemble strategy: As can be seen from Fig. 2, the Bayesian-based ensemble strategy always performs much better than the majority voting ensemble strategy.

Therefore, we can conclude the following suggestions for the general procedure of SVM-based ensemble learning system shown in Fig. 1:

(1) In Stage II, individual classifier construction should employ as diverse individual classifier as possible;

(2) In Stage III, ensemble member selection strategy should select CFS strategy;

(3) In Stage IV, ensemble classifier construction should use Bayesian-based ensemble strategy in order to obtain better performance than any of individual SVM models.

For the second motivating goal of this experiment, to evaluate the effectiveness of the SVM-based ensemble model we compare two typical ensemble approaches. Fig. 3 illustrates the results. Note that Fig. 3 shows the total accuracy of E_3, E_4, LogR ensemble and ANN ensemble.

Because E_3, E_4, LogR ensemble and the ANN ensemble are created by employing the same kind of ensemble members, in variation 2, namely changing the training data set, we just compare the total accuracy of E_3, E_4, LogR ensemble and the ANN. From Fig. 3, we can easily find that both E_3 and E_4 perform much better than LogR ensemble and ANN ensemble, indicating that the SVM-based ensemble models can be used as an effective tool to identify high risk customers in CRM. The main causes leading to this phenomenon reflects two aspects. On the one hand, SVM is a competitive classifier; it is constructed in terms of the structural risk minimization principle, which makes SVM possess power generalization capabilities [13]. On the other hand, the LogR model is a class of linear model, with which it is difficult to capture the nonlinear relationship between customer credit and customer behavior; while ANN often traps into the local minima, which influences the performance of ANN classifiers.

4 Conclusions

In this study, we proposed an SVM-based ensemble learning approach to help enterprise managers effectively manage customer relationships from a risk avoidance perspective. At the same time, to build an effective CRM system for identifying high-risk customers, we focused on studying the effects of ensemble members' diversity, ensemble member selection, and final ensemble strategies on the performance of the proposed SVM ensemble based CRM system respectively. Through experimental analysis, we have found that: (1) increased diversity of individual classifiers can improve the performance of the SVM-based ensemble models; (2) CFS consistently performs the best amongst the three strategies of ensemble members' selection; (3) The Bayesian-based ensemble strategy consistently performs much better than the majority voting ensemble strategy. These results and findings also demonstrate the effectiveness of the SVM-based ensemble models relative to other ensemble approaches, such as logistic regression ensemble and neural network ensemble models.

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