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# Evaluation of consumer satisfaction based on binary decision trees

## Evaluación de la satisfacción de consumidores basado en árboles binarios de decisión

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**ABSTRACT:**
This article presents the original approach to the assessment of global customer satisfaction of business organizations based on data mining. The basis of the approach is the mechanism of machine learning, which includes two phases: training and testing. Given the qualitative nature of initial information, the logical algorithm of machine learning was chosen, basing on the construction of the classifying binary decision trees and allows to restore the non-linear relationship between the target variable and features. Logic algorithm allows: 1) to include random customer satisfaction to one of the classes, which are prede-fined in advance, depending on the preferences of company management; 2) to measure the weight / im-portance of each criterion and rank them in order of importance; 3) to construct an action diagram of the strengths and weaknesses of a company for each criterion. The proposed method is brought up to specific steps and is illustrated by a numerical example.
**Keywords:** Satisfaction consumption, decision tree, classification algorithm, machine learning

**RESUMEN:**
En el presente artículo se propone un enfoque original para evaluar la satisfacción global de consumidores de organizaciones empresariales, basado en la metodología de exploración de datos (minería de datos). El enfoque se basó en el mecanismo del aprendizaje automático, que incluye dos partes: capacitación y examen. Habida cuenta del carácter cualitativo de información básica, un algoritmo lógico de aprendizaje automático fue elegido, que se basa en construcción de árboles binarios de decisión para la clasificación y que permite recuperar las relaciones no lineales entre una variable objetiva y sus que características. El algoritmo lógico permite: 1) incluir un consumidor arbitrario a una de las clases de satisfacción predeterminadas según las preferencias de la Dirección de una empresa; 2) medir el peso/la importancia de cada criterio y graduarlos en orden creciente de importancia; 3) hacer una diagrama de acciones, que muestra los puntos fuertes y débiles de una empresa según cada criterio. La metodología propuesta es llevada a los casos concretos y fue ilustrada con un el ejemplo numérico.
**Palabras clave**: Satisfacción de consumidores, árbol de decisión, algoritmo de clasificación, aprendizaje automático

## 1. Introduction

Measuring customer satisfaction is one of the most important issues, regarding commercial organizations of all types. The philosophy of the client-focused approach of the modern business organizations and implementation of the basic principles of continuous improvement justify the importance of measuring and analyzing the customer satisfaction. Currently, satisfaction is seen as the most reliable characteristics of the feedback from customers, bearing in mind that it reflects the preferences and expectations of our customers effectively, meaningfully and objectively.  Therefore, today's customer satisfaction can be seen as a possible quality standard in commercial organizations. On the other hand, it is impossible to continuously motivate employees of a company by non-material and abstract notion. For this reason, the satisfaction must be moved to the range of measurable parameters directly related to the people's work activity, i.e. it must become a factor, which can be understood and influenced. The measurability provides achieving and implementing the goal for all staff involved in every stage of the process of customer service, whereas the using of a measuring system will help in identifying potential differences in perception of the quality of service between customer and management of a business organization.

The purpose of this work is to suggest the method for evaluating the global customer satisfaction of a company basing on their private judgments upon assigned criterion, to estimate the contribution of each criterion to results.

## 1.1. Basic methodological approaches

Various approaches to defining the customer satisfaction can be found in today's literature. The most popular of them are based on satisfaction of customer expectations. As noted by Gerson (1993), Hill (1996), Oliver (1997) and Vavra (1997), satisfaction is a standard of how the offered "total" product or service fulfils customer expectations. Extensive research in the considered field have identified alternative approaches to estimation and analysis of satisfaction from multiple perspectives. The simplest method of analyzing polling data of satisfaction is estimation of frequency of customer answers to specific questions, which are considered critical. More precisely, depending on the applied scale, percentages of satisfied and dissatisfied customers are calculated and used as an indicator of effectiveness of a company. In the event that in the survey of satisfaction metric variables are used, the common satisfaction index can be estimated basing on the customer judgments about satisfaction and importance for individual characteristics of a product or service. The customer satisfaction index, or CSI, is calculated using a weighted sum formula (Hill, 1996):

$$CSI = \sum \bar{\beta}_i \cdot \bar{x}_i$$

Where $\bar{x}_i$, $\bar{\beta}_i$ – are the average scores of the satisfaction/performance of characteristic *i* (criterion) of a product/service. The given methods of calculating of the descriptive statistics are unable to provide an in-depth analysis of the customers satisfaction. Nevertheless, they can be used whether in a preliminary analysis, or in addition to other quantitative models.

The more in-depth analysis includes statistical methods of data analysis. Multiple regression analysis is one of the most widely used statistical methods for analysing customer satisfaction data (Grisaffe, 1993; Mullet, 1994). The method is used to study the relation between the satisfaction/performance of the total set of or service's characteristics (independent variables) and the overall customer satisfaction judgment (dependent variable). The general form of multiple regression equation is as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_m X_m,$$

Where *Y* is the overall customer satisfaction judgment, $X_i$–is the customer satisfaction/performance of characteristic *i* (criterion) of a product/service, $\beta_i$ –are the estimated regression coefficients (OLS-estimations), *n* is the number of product or service characteristics.

Let us stress the following features of using linear regression analysis in tasks of evaluating the customer satisfaction. All the variables in the linear model should be metric, otherwise multiple regression analysis should not be performed. Particularly in the case of ordinal variables, the arbitrary codification of the scales may lead to significant inconsistencies. In addition, if model variables are measured in different scales, a normalization procedure is necessary. The main problems and critic of this particular approach are focused on quantitative estimation of satisfaction data and multicollinearity among independent variables $X_i$. Even the using of the metric scale implies that the variables in a model are continuous, which is often incompatible with a type of information gathered.

The other statistical method widely used in customer satisfaction data analysis is factor analysis. It is a statistical method used to describe variability among observed, correlated variables in terms of a potentially lower number of unobserved variables called factors. The purpose of the method is to examine the laws of correlations between the characteristics of a product or service. The main form of the factor analysis equation binding the set of variables with a minimum quantity of factors is (Warne, Larsen 2014):

$$X_i = a_{i1} F_1 + a_{i2} F_2 + ... + a_{im} F_m, i = 1,2,...,n,$$

Where $X_i$ the customer satisfaction/performance of characteristic *i* (criterion) of a product/service, $F_j$ is the factor *j*, $a_{ij}$ – are the estimated coefficients, *m* is the number of factors, *n* is the number of characteristic *i* (criterion) of a product/service (Warne, Larsen 2014).

The class of conditional probability models is one of important quantitative methods of measuring customer satisfaction, in which the ordinal type of dependent variable is taken into account. The mentioned models estimate the probability of customer belonging to a certain group (e.g., satisfied customers, dissatisfied customers etc.) (Andersen et al., 2014; Agresti, 1996). One of the basic types of conditional probabilistic models is linear probability model, as well as logit and probit models. The common form of the logit regression model for a binary variable *Y* is given below:

$$P(Y = 1 | X) = \frac{e^z}{1 + e^z}, \ z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n$$

Where P(*Y*=1|*X*) is the probability of customer belonging to a certain group (e.g., satisfied customers) at the specified value of $X_i$, which is the customer satisfaction/performance of characteristic *i* (criterion) of a product/service.

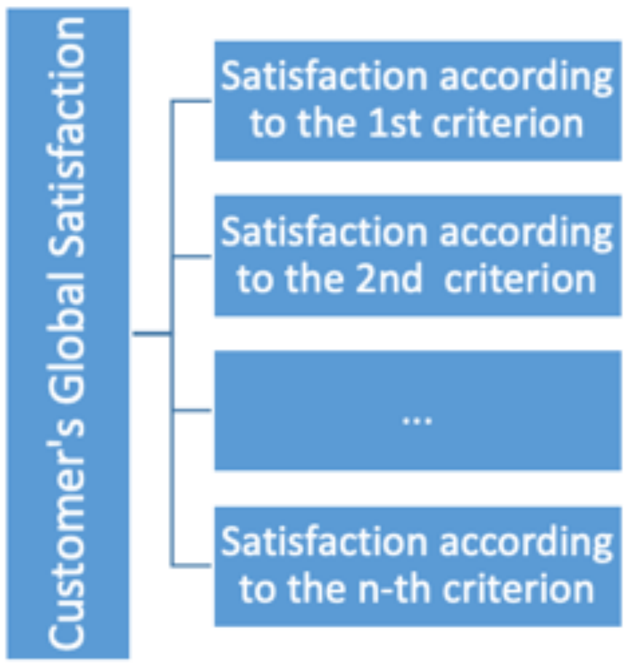
The conditional probability models is generalized in case the dependent variable takes several (more than 2) values characterizing the customer satisfaction. It is supposed that the resulting value has an ordinal type and takes values from minimum to maximum level of the global customer satisfaction. This type of models has served as a base of the Multicriterion Satisfaction Analysis (MUSA method) developed by the scientists from the University of Crete in their cycle of works (Siskos, Grigoroudis, et al. 1998, 2002, 2003, 2010). The advantage of the method is that it takes fully into account the qualitative form of customer judgments and preferences. The necessary information is received through questionnaires, in which customers evaluate the service provided. Another advantage is that this method allows obtaining the weights of criterion. For this reason, a researcher has an opportunity to estimate the relative importance, which respondents attach to different aspects of the service efficiency.

In conclusion, we should mention a group of methods, which are basing on systems of fuzzy output, designed to convert the values of the input variable based on using fuzzy production rules. These rules are implemented in the form of premises or conditions set out in the form of fuzzy linguistic propositions. To obtain the estimation of the global customer satisfaction, it is necessary to form full and non-controversial system of logical rules, consisting of criterion conditions (Arinichev, et al. 2016).  One of the advantages of the method is the ability of unsupervised learning of decision-making systems. Still, the set of rules is based on expert opinions and is subjective in nature.

# 2. Methodology

Following the approaches represented in the works (Siskos, Grigoroudis), we shall address the global customer satisfaction of a company as an aggregation of particular customer preferences, expressed as judgments upon assigned criterion relative to the output of a product/service (fig. 1). Types and numbers of such criterion should be defined in advance taking into account the activity of the organization in question.

**Figure 1**
Aggregating of company customers preferences



The methodology of the preferences aggregation is based on machine learning approach used for identification of meaningful patterns in particular customer judgments in such a way that the global criterion would become harmonized with particular criteria as far as possible. According to this approach, each customer *x* is asked to express his opinion, namely to measure the level of his global satisfaction $y_i = f(x_i) \in Y$ and satisfaction regarding particular criterion $f_j(x_i)$, where $i = \overline{1,m}$ is an ordinal number of an object (customer), $j = \overline{1,n}$ is an ordinal number of particular criterion. Then the vector $(f_1(x_i), f_2(x_i), ..., f_n(x_i)) \in X$ specifies full feature vector of an object. We shall examine the level of global and particular satisfaction upon each particular judgment in the ordinal scale *D*= {«Very satisfied», «Satisfied», «Neutral», «Dissatisfied», «Very dissatisfied»}. In fact, the given scale is not free from criticism and chosen by us for specifying the research being conducted. In the common case it can be chosen arbitrarily in accordance with the wishes of the management of an organization. For example, assuming Y = {-1, 1} as the set of possible answers, we get a problem of classification whose solution can be interpreted as an answer to the question: will the customer address the company once again (*y* = 1) or not (*y* = -1). In our example, we have also a problem of classification into five disjoint classes.
To provide a high quality of classification and to establish an association between particular judgments and the global customer satisfaction, which is caused by the internal logic of a model, we shall split the sample of all the customers interviewed (*X*,*Y*) on two parts: training sample ($X^l$, $Y^l$) and test sample ($X^t$, $Y^t$) and use the next two-step procedure:

**Training stage**. The classification algorithm is based on the training sample $X^l$ using a method $\mu$: $a = \mu(X^l \times Y^l)$. At this step, the inner parameters (coefficients) of the classifying algorithm, which divides all the customers on the satisfaction classes, is being optimized. Metaparameteres are chosen in advance and shall not be changed during the model training.

**Testing stage**. The trained algorithm $a = \mu(X^l \times Y^l)$ is tested on the objects, which were not included in a training sample, and then the quality of classification is being estimated. If the algorithm shows low summarizing ability in the tasting data, for instance, because of the «retraining» effect of a model, then a return to the first step of the machine training procedure is done, where a choice of the new parameters of a model is made, after which the algorithm is trained again.
We shall choose the frequency of the "accurate" answers of the algorithm in the testing data as a classification quality metric:

$$accuracy(a, X^{test}) = \frac{1}{|X^{test}|} \sum_{i=1}^{|X^{test}|} [a(x_i) = y(x_i)]$$

Then the task of evaluating the global customer satisfaction as a result of aggregating private judgments of customers is to maximize the metric *accuracy* using all the algorithms *a* from assemblage *A*:

$$accuracy(a, X^{test}) \to \max_{a \in A}.$$

Taking into account the specificity of the task and the qualitative character of the customer judgments, the family of logical algorithms of classifying the customer satisfaction level was chosen as *A*. Each algorithm of the family is a binary tree (acyclic graph), each inner node of which $v \in V_{внутр}$ is assigned with a predicate $\beta_v : X \to \{0,1\}$, each of the leaf (terminal) node $v \in V_{лист}$ – label of the class $c_v \in Y$. In the present work one-dimensional predicates of the type $\beta_v(x) = \{x_j \le \theta_j\}$ are used, where $\theta_j$ is a certain threshold of *j*-th attribute of an object.

Binary decision algorithm starts from the root node $v_0$ and calculates the predicate value $\beta_{v_0}$. If it equals zero, then the algorithm moves to the left child node, otherwise – to the right, calculates the predicate value in a new node and makes a transition whether to the left, or to the right. The process continues until the leaf node is achieved; the algorithm returns the class, which was assigned to this node.
To build a decision tree, the recursive procedure *Induction of Decision 3 (Learn ID3)* was chosen, the pseudocode of which is represented on the fig. 2.

**Figure 2**
The recursive procedure of building binary decision tree

| | | |
|---|---|---|
| 1. | **FUNCTION** *LearnID3* $(S \subseteq X^l)$ | |
| 2. | **IF** $\forall s \in S \Rightarrow y_s = c \in Y$ | *if all the subsample objects are in the same class;* |
| 3. | **RETURN** $v,\ c_v = c$ | *return a new leaf node and assign a class label to it;* |
| 4. | $\beta = \arg\max_{\beta} I(\beta, S)$ | *find a predicate with maximum informativeness;* |
| 5. | $S_0 = \{x \in S : \beta(x) = 0\}$ <br> $S_1 = \{x \in S : \beta(x) = 1\}$ | *split the sample into two subsamples* $S = S_0 \cup S_1$ *using the maximum informativeness predicate β;* |
| 6. | **IF** $S_0 = \varnothing$ **OR** $S_1 = \varnothing$ | *if splitting has not occurred;* |
| 7. | **RETURN** $v,\ c_v = c$ | *return a new leaf node; assign a label of the object class of which is larger in the subsample;* |
| 8. | $v : \beta_v = \beta$ | *create a new inner node and place a predicate in it;* |
| | $L_v = LearnID3(S_0)$ | *build left subtree;* |
| | $R_v = LearnID3(S_1)$ | *build right subtree;* |
| 9. | **RETURN** $v$; | *Return decision tree;* |

The most important step of the mentioned procedure is searching the predicate with maximum informativeness. A wide variety of methods of building the decision trees arise, when defining a predicate which would outline some group of classes from all the other classes, depending on the choice of branching criterion.

With the purpose of concretizing the research, the authors have used Gini criterion, which indicates how many pairs of objects belong to the same class will simultaneously move whether to the left, or to the right child node (the values of their predicates are congruent):

$$I(\beta, X^l) = \#\{(x_i, x_j) : y_i = y_j, \beta(x_i) = \beta(x_j)\}.$$

A definite advantage of binary decision trees is the visibility of the modelling results. In accordance with the logical conditions in graph nodes, each customer moving from the initial node, can be unequivocally related to one of the global satisfaction classes. The other important feature of the suggested algorithms is their ability of evaluating the contribution of each criterion to the result. In other words, the procedure allows to obtain estimations of the importance of each criterion on a scale from 0 to 1, which allows to compare criteria with each other and choose "the most important" of them.

If we compare average satisfaction indexes of particular criteria with their importances, we can depict the results of modelling on a diagram map (fig. 3), which not only demonstrates strengths and weaknesses of the customer satisfaction, but also contributes to the elaboration of strategic management decisions (Siskos, Grigoroudis). The diagram is divided on four quadrants depending on the importance of a criterion along the axis OX (high/low) and the average satisfaction along the axis OY (high/low), which can be used for classifying the next actions:

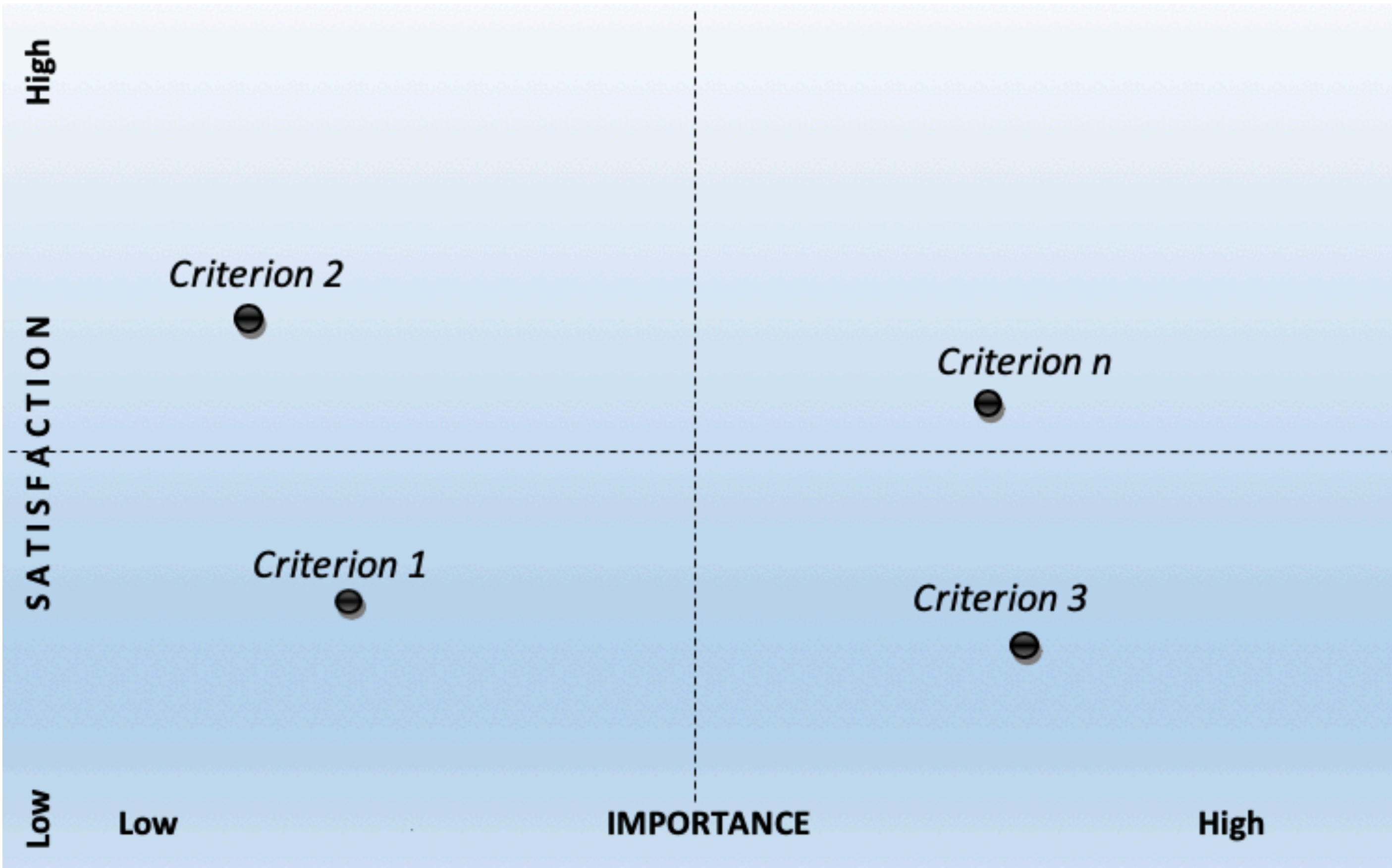
1- *Status quo* (low performance and low importance): Generally, no action is required, given that these satisfaction dimensions are not considered as important by the customers.

2- *Leverage opportunity* (high performance/high importance): This area can be used as advantage against competition. In several cases, these satisfaction dimensions are the most important reasons why customers have purchased the product/service under study.

3- *Transfer resources* (high performance/low importance): Regarding the particular satisfaction dimension, company's resources may be better used elsewhere (i.e. improvement of satisfaction dimensions located in the action opportunity quadrant).

4- *Action opportunity* (low performance/high importance): These are the criterion that need attention; improvement efforts should be focused on these, in order to increase the global customer satisfaction level.

**Figure 3**
Importance/satisfaction diagram




## 3. Results

The authors have chosen four criteria for approbation of the suggested methodology (staff, product, service and availability) for a "fast food" store (fig. 4).

**Figure 4**
Hierarchic structure of satisfaction criteria in a «fast food» store


In table 1 a part of a training sample is represented, which contains data from customer surveys upon each particular criterion and the global satisfaction in common.

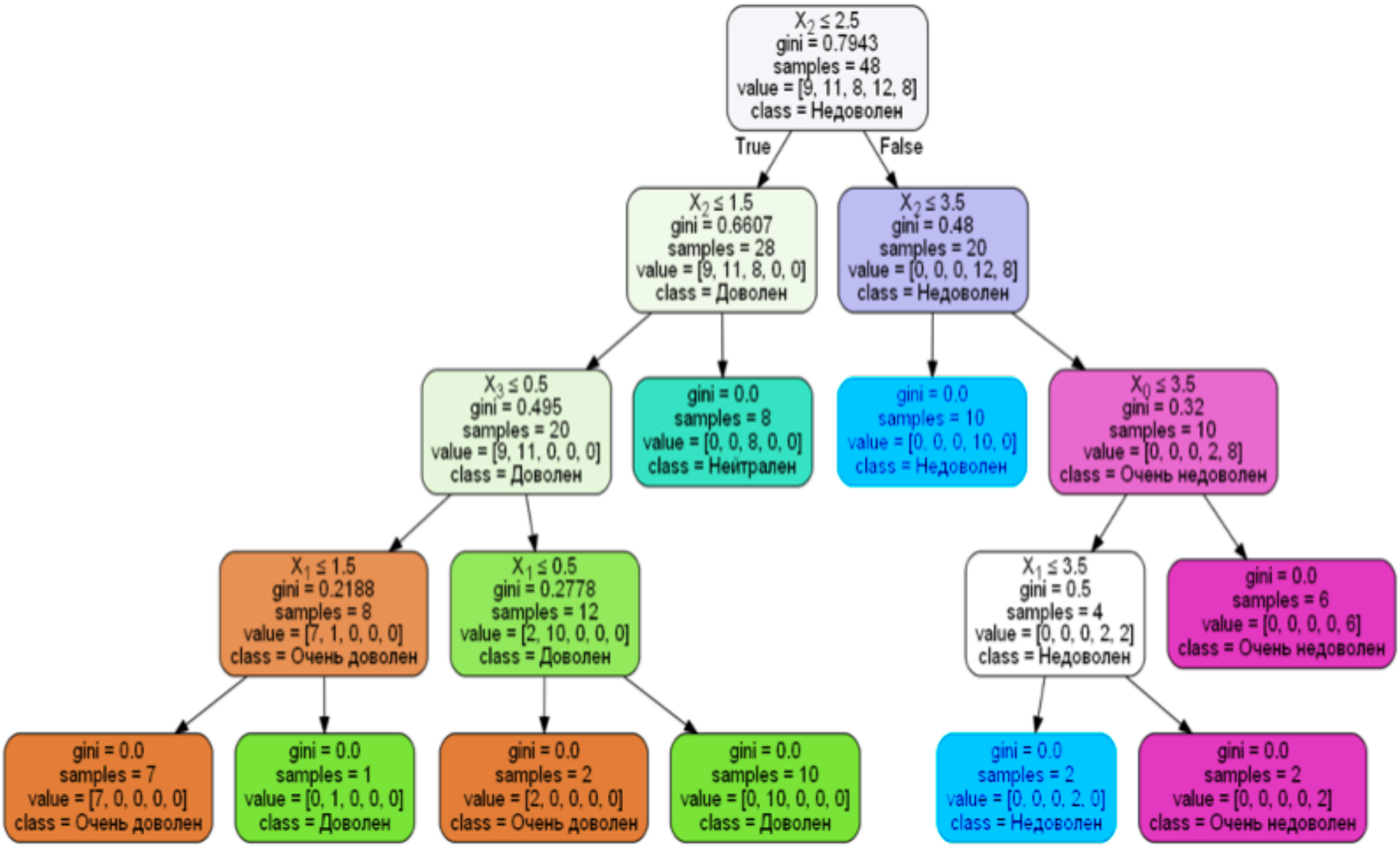
To simplify the procedure of relating an arbitrary customer to one of the classes of aggregated satisfaction, the labels of classes on an ordinal scale *D* for particular criteria were encoded to numerical values from 0 to 4, which also allowed to calculate average satisfaction indexes.

**Table 1**
Training sample of the customer survey on four types of criteria

| Customer | Global satisfaction | Personnel | Product | Service | Access |
|---|---|---|---|---|---|
| 1 | Very dissatisfied | Dissatisfied | Very dissatisfied | Very dissatisfied | Very dissatisfied |
| 2 | Very dissatisfied | Very dissatisfied | Dissatisfied | Very dissatisfied | Dissatisfied |
| 3 | Dissatisfied | Dissatisfied | Dissatisfied | Dissatisfied | Very dissatisfied |
| 4 | Dissatisfied | Neutral | Neutral | Dissatisfied | Dissatisfied |
| 5 | Neutral | Neutral | Neutral | Neutral | Neutral |
| 6 | Satisfied | Satisfied | Neutral | Very satisfied | Satisfied |
| 8 | Satisfied | Dissatisfied | Very satisfied | Satisfied | Satisfied |
| 9 | Very satisfied | Very satisfied | Satisfied | Very satisfied | Neutral |
| 10 | Very satisfied | Dissatisfied | Very satisfied | Very satisfied | Very satisfied |

As a result of using a procedure ID3 a binary decision tree was built (fig. 5), each node of which contains an inequality-restriction, basing on which a branching of the process of making decisions is proceeded; the volume of a customers subsample, related to the corresponding node as a consequence of branching; the value of Gini criterion, as well as the text label of the global satisfaction class.

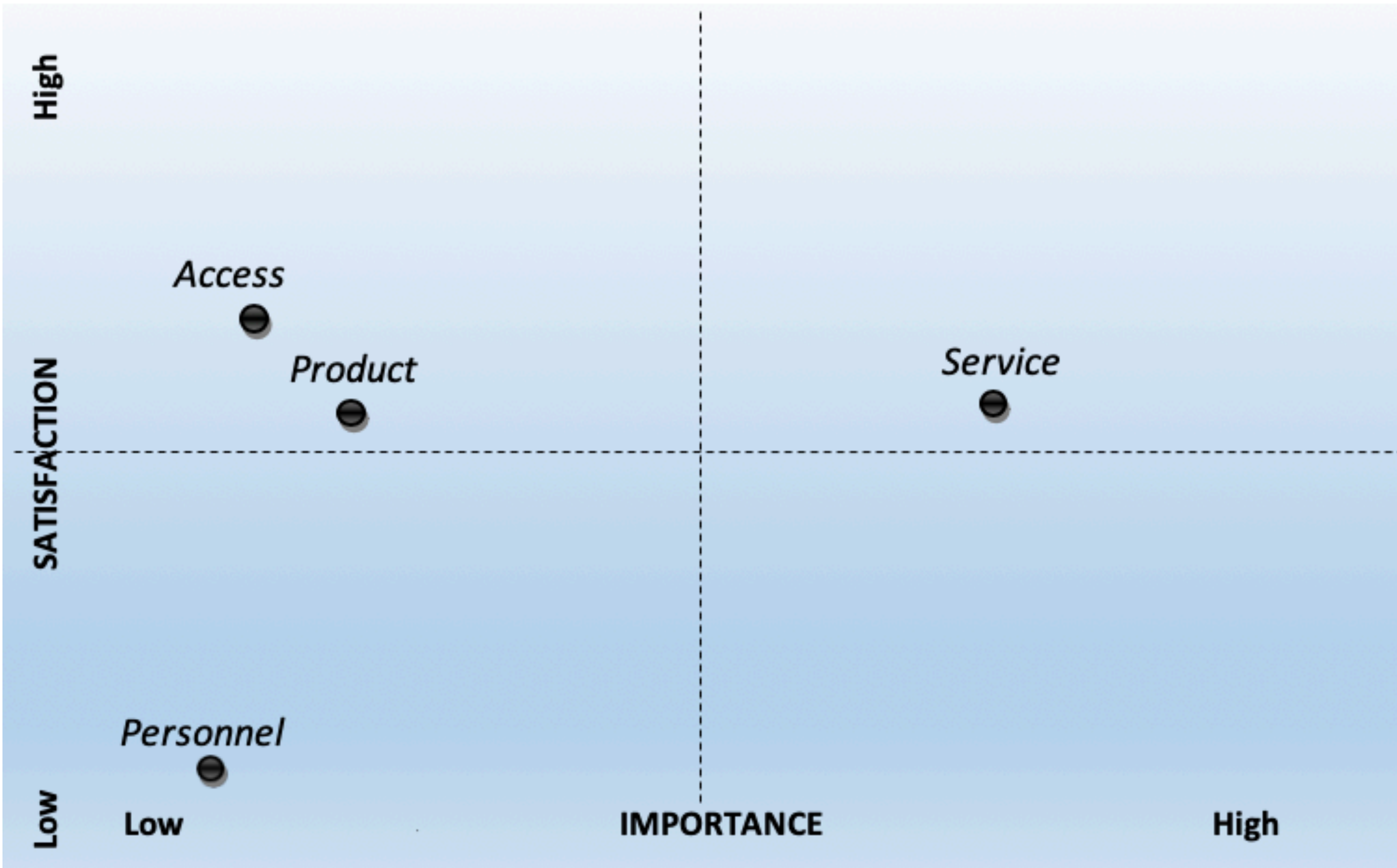
**Figure 5**
Binary decision tree of classifying the objects




As was noted above, one of the features of decision trees is the ability to evaluate the importances (weights) of all the aggregated characteristics (criteria) on the basis of how sufficient will the quality criterion improve through using of this characteristic in tree nodes. The weights of criteria in the present example for «Staff», «Product», «Service» and «Availability» equal respectively (0,031; 0,186; 0,656; 0,126). It can be seen that the global customer satisfaction is formed more under influence of the particular satisfaction of the store service and less by its staff.

The analysis of the importance diagram (fig. 6) shows that none of the criteria has entered the critical area (the right-lower quadrant), which requires immediate management decision on advancement of production activities of the model organization. Nevertheless, if the company wishes to create competitive advantages, the criterion with the lowest values of the satisfaction indexes may be increased. In this case, the efforts of the company management may be focused on the criterion "Staff" with the purpose of moving it to the top left quadrant.

**Figure 6**
Importance/satisfaction diagram for the «fast food» store




## 4. Conclusions

For the last decades the organizations of all for all the types and sizes come to understanding of the importance of definition “customer satisfaction”. Nowadays it is far cheaper to retain the existing customers than to attract the new ones. For this reason, the customer satisfaction has become the key operational objective for many organizations, whereas the presence of the customer satisfaction barometer is today’s necessary condition for applying the basic principles of the continuous improvement of a company and the concept of the total quality management.

The article suggests an original method of estimating the global customer satisfaction based on aggregating of evaluations of customers private judgments on several characteristics (criteria) of an organization, which reflect strengths and weaknesses of an enterprise. The procedure is based on the principles of the machine training and splits on two stages (training and test), which repeat until the functionality of a quality achieves a sufficient quality of classifying the customers on groups. Taking into account the quantitative character of customer judgment, the authors have suggested a family of logical algorithms (binary decision trees) which on the one hand demonstrate visibility and transparency of making decisions; on the other hand, they make it possible to evaluate the weight (importance) of each criterion. The method is brought up to the concrete steps, which allows to integrate it to the common approach to quality management in companies. Moreover, a comparative analysis of modelling results and particular satisfaction indexes of a company can help in making effective management decisions in the process of developing crisis strategies in business.

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