Customer Churn Prediction in the Software by Subscription models IT business using machine learning methods

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Abstract

The article presents the results of research related to the problems of development of IT products based on the Software by Subscription model in the IT sphere. Operating in market conditions, such enterprises are forced to develop modern IT products to support small and medium-sized businesses based on the interaction of many potential external customers (users of the IT system), who later, under favorable conditions, become customers of these enterprises. At the same time, the very nature of the Software by Subscription company is largely determined by its average client, and is a topic played out in many empirical rules of Software by Subscription metrics. To improve the efficiency of customer interaction with SaaS companies, the authors proposed a hypothesis about the possibility of using various forecasting methods in machine learning. A comparative characteristic of the use of different models and algorithms for predicting the outflow of customers for an IT company is carried out. At the same time, the development of innovative IT products should be carried out with the fullest satisfaction of the interests and needs of all major stakeholders. The article offers a mathematical description of the model and method of modeling these interactions.. To conduct chain training, the Python functionality is used, with the processing of user activity data sets. The analysis is carried out and conclusions are made about the effectiveness of the proposed approach.

Keywords [1]

Software by Subscription, random forest algorithm, IT company, Customer Churn Prediction

1. Introduction

Customer Churn Prediction is one of the classic problems in deep data analysis (data mining). IT companies have long analyzed customer usage patterns to predict customer churn. Many other industries, such as banking, regularly analyze customer behavior to predict their satisfaction and level of renewal [4].

The software by Subscription model allows software vendors to collect data about customer usage that is not available to traditional software vendors [1,2].

Although the market for Software by Subscription and cloud computing in general is growing rapidly, however, as far as we know, from a scientific and practical point of view, the problem of outflow in B2B Software by subscription projects has not been sufficiently studied and the application of existing methods for analyzing customer outflow in the field of B2B Software by Subscription has not been fully done to resolve this issue. Despite significant international experience, domestic IT companies have their own peculiarities of formation and development, which is due, on the one hand, to globalization processes, and on the other-to the peculiarities of the National Economy [7]. The low speed of testing IT products, insufficient development of the technological base, and a high level of

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competition in the industry cause the main problems of domestic IT startups, namely, the slow pace of their creation and entry into the market with ready-made products [3].

The software by Subscription business model depends on strong and long-term customer relationships. If customers are not satisfied or are not reminded of the price that the IT company's service regularly provides, they cancel their subscription. The company, in turn, should focus on retaining customers for as long as possible, developing these relationships. The range of predictive capabilities of machine learning should help it do this [11].

Content streaming services are by far the most well-known examples of the software by Subscription business model. Companies like Netflix and Spotify have built incredibly successful businesses using their subscription growth potential. However, not everyone was able to repeat it, even Adobe in 2018 had some financial losses, not correctly calculating its subscription offers for software such as Photoshop [8].

While some companies do this by monetizing content and demonstrating their value through the entertainment experience they offer, others compete in narrower niches of industrial and desktop software, which requires companies to put much more effort into promoting, advertising, and retaining customers than just good content. Accurate forecasting of customer outflows and building a balanced marketing and financial policy of an IT company based on this will help an IT company solve this complex and vital task [15].

2. Related Works

Euler [16] developed a decision tree to identify the types of telecommunications customers that are most likely to be solved. Euler used the capabilities of the KDD MiningMart data preprocessing system to obtain predictable characteristics that were not present in the original data. Kusment and Van den-Paul used support vector machines to improve churn prediction performance for the newspaper subscription service [17]. The results of this work show that the interaction between customers and the supplier is important for outflow analysis. Kusment and Van-den-Paul continued to study customer-provider interaction by adding emotions from customer email to their model [18]. [4] determined the predictive characteristics of customer churn and found that decision trees outperformed neural networks and regression in terms of overall accuracy.

To expand the analysis, numerous studies have explored various machine learning algorithms and their potential for outflow modeling. Since predicting whether a client will be lost is not a binary classification problem, several models have been tested, such as logistic regression [19], decision trees [20], random forest, supporting vector machines, and neural networks [21].

Considering the development processes of IT project products, it is necessary to consider the development directions of companies themselves with Software by Subscription [22] and B2B [23] business models. Although our review points to numerous studies on software by Subscription, most of the work tends to focus on multiple programs. In particular, previous subscriber subscription work is usually based on subscriber data in mobile phone areas [24], credit cards [25], and internet service delivery [26].

3. Proposed methodology

The purpose of this article is to analyze modern models and methods for predicting customer churn using machine learning, which can be applied to the activities of B2B Software by Subscription IT companies. This will help companies and their teams to create, market and scale IT products more efficiently, which can not only increase the efficiency of the enterprise due to the competence of personnel, but also generally strengthen Ukraine's position in the global innovation market.

In this article, we used the analysis of customer outflow in telecommunications as a basis for studying the software by Subscription industry. Although there are differences between these two industries, they actually have a lot in common. The paper presents a literature review, a detailed description of the context of the problem, a comparison of software by Subscription and telecommunications providers, an example of an experiment, and outlines opportunities for future research in the dissertation using neural networks to build effective algorithms for solving further problems.

Software by Subscription models usually mean that the customer installs the product, as when selling software on the spot, but pays the supplier in stages, rather than in full upfront. The provider does not bear the costs of hosting or integration with other applications. The transition to the subscription model is often the first stage for traditional software development companies moving to the Software by Subscription model [9].

The validity period of the licenses is similar, since the client pays for the installed software for a certain period, usually one, two or three years. Subscription models usually include maintenance and updates, as in SaaS, but urgent licenses do not. However, there is no rigid generally accepted definition of Subscriptions compared to fixed-term licenses, as it is clear that IT companies use these terms interchangeably [13].

Both subscription and fixed-term (and SaaS) payment contracts may or may not include the right to cancel and refund fees already paid. These conditions affect revenue recognition and customer retention.

In local software, the supplier does not bear the costs of hosting the software, but must send the software to the customer, so the distribution costs are different. Local companies are often more likely to use an affiliate channel to distribute, install, and support their sales. While SaaS vendors are also expanding the use of channel sales, the channel still typically accounts for a smaller percentage of total revenue [6].

According to experts in this field, SaaS and similar models do not simplify licensing metrics. If we look at "pure SaaS solutions" like Salesforce, there are a few things to consider. An article published by the BSA (navigating the cloud :why managing software assets is more important than ever) highlights the risks and pitfalls of SaaS in terms of license management:

- Software components: some SaaS solutions include plugins or other user-side software that requires proper licensing and management
- Unauthorized use: violation of geographical restrictions, shared logins, incorrect logins (for example, administrator accounts, not regular accounts), providing logins to third parties, generating value from the SaaS system, and sharing with others who do not have access
- Warehouse (paid but not used software): the use of licenses should be constantly monitored to identify unused licenses
- User profile definition: given the "multi-user rental" architecture, only one version of the product is deployed for the entire organization (depending on the company size, product characteristics, and user requirements) and cannot be changed until the end of the contract.

In another case, there may be a case of a SaaS architecture “for one tenant”. In this case, different configurations are possible, according to the requirements of each user. In the case of software by Subscription or “quasi-SaaS”, such as Adobe Creative Cloud, the license rate does not change compared to the old perpetual model (for example, by installation). This means that if these licenses are not properly managed and controlled, the risk of compliance may still be high [7].

Contrary to popular belief about software by Subscription licensing, software asset management practices are still very important in IT departments and should be reviewed to properly handle new license models [28].

Software as a Service (SaaS) defines the financial/contractual, as well as the delivery aspects of the" product "and the" product " of the supplier/customer relationship. SaaS revenue is based on customer subscriptions to access a "service" hosted in the cloud. The SaaS business model for a supplier affects the entire business and every department, from strategy to finance, sales and marketing, research and development, customer management and business systems needed to manage and track a variety of activities (Fig.1).

Fixed-term licenses, sometimes called subscriptions, refer to the financial terms of the relationship between the supplier and the customer. According to the fixed-term license, the customer pays the supplier in increments over time, but installs the product, as when selling software on the spot. The provider does not bear the hosting costs. The transition to a fixed-term license or subscription model is often the first stage for traditional software companies moving to the SaaS business.

It is observed that companies use the terms "fixed-term license" and" subscription license "interchangeably, but" Fixed-term license " is usually applied to a specific term, such as a license for two or three years, which then expires.

The local software is delivered to the customer and installed on the customer's website. Payment is usually made in advance with annual maintenance and maintenance fees. The supplier is responsible for problems with the product and may be responsible for interacting with other customer systems. The client is responsible for paying for and managing everything necessary for the use of the software.

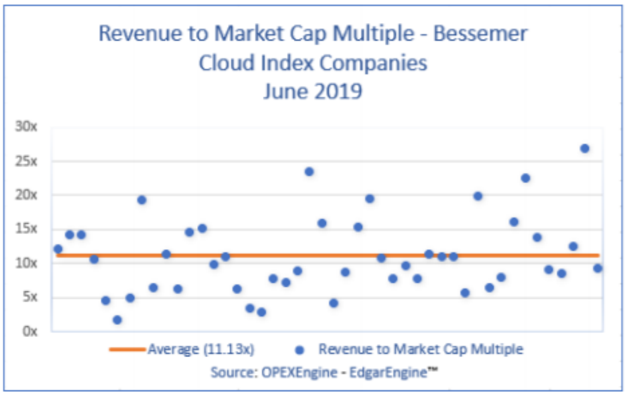

Figure 1: Revenue to Market Cap Multiple [4]

One of the most powerful ways to grow software by Subscription is through "net negative MRR churn". With a negative outflow, the company's it revenue generated from existing customers month after month outstrips the revenue lost as a result of cancellations and downgrades. The lower the user outflow, the easier it is to achieve a net negative MRR outflow.A negative outflow is observed when some of your users start paying more: they switch to a more expensive tariff, buy additional modules, extensions, and so on.

When analyzing B2B companies, attention was drawn to this impressive difference in revenue. A business with a negative outflow is almost 3 times larger than the same one with a standard outflow of 2.5% (note that this indicator is considered very good). And a business that users do not leave at all has only 60% more revenue than the same one with an outflow of 2.5%. Obviously, negative outflow is the most powerful growth accelerator [7].

When calculating the outflow rate, this was done in order to gain a deeper understanding of your customers and why they are leaving your product. Improve this, we get improve customer retention rates (from English Customer Retention) in order to strengthen your business in the long run.

Customer Retention is a company's ability to maintain a long-term relationship with a customer. A high rate means that your customers are happy to return for a new purchase and recommend you to their friends. Customer Retention rate formula:

$$Crr = \frac{Customer\ at\ end\ of\ period - Customer\ acquired\ during\ period}{Customer\ at\ the\ start\ of\ the\ period} 100, \qquad (1)$$

where Crr – Customer retention rate.

Customer churn can result from low levels of customer satisfaction, aggressive competitive strategies, rejection of new products, etc.churn models are designed to detect early signals of customer churn and recognize those who are highly likely not to use services.

For machine learning methods, it is necessary to collect training data, the main task of which is to describe the client in as much detail as possible. The following indicators can be used for this purpose:

- Socio-demographic data
- Transactional data (the number and amount of transactions for the period, grouped by different criteria, etc.)
- Product and segmentation data (changes in the number of contracts, belonging to the bank's internal segmentation group, etc.).

The target variable showing the probability of outflow obviously directly depends on changes in the client's transaction activity, as well as on the client's category and subscription type. After identifying a group of customers with an increased risk of outflow, methods of retaining customers are applied by providing profitable promotions, offers, and so on.

From the analysis of machine learning methods, the optimal one for predicting customer outflows will be the one that most accurately corresponds to the relationships between the data in the sample that characterizes the type of business [29].

The experiments were conducted using methods implemented in the Python programming language. The effectiveness of using methods is determined by the accuracy of classification, i.e. the proportion of objects that actually belong to the class relative to all objects that are assigned to the class based on the results [12].

To solve this problem, we used a deep neural network. It is defined as a neural network with several layers. In deep neural networks, each layer of neurons is trained on the properties / outputs of the previous layer. Thus, we were able to create a hierarchy of objects to increase abstraction and test complex hypotheses.

Deep learning based on libraries TensorFlow, PyTorch, MXNet, and Chainer are usually used to predict customer churn in B2C. In our B2B study, we used scikit-learn and TensorFlow. Code snippets for initial data processing and Tensor creation are shown in Fig. 8.

The tocategoric () function was used to convert categorical properties to one. This made it possible to convert String values to numbers and used tf.onehot () for creating vectors.

```
const toTensors = (data, categoricalFeatures, testSize) => {
  const categoricalData = {};
  categoricalFeatures.forEach(f => {
    categoricalData[f] = toCategorical(data, f);
  });

  const features = [
    "SeniorCitizen",
    "tenure",
    "MonthlyCharges",
    "TotalCharges"
  ].concat(Array.from(categoricalFeatures));

  const X = data.map((r, i) =>
    features.flatMap(f => {
      if (categoricalFeatures.has(f)) {
        return categoricalData[f][i];
      }

      return r[f];
    })
  );

  const X_t = normalize(tf.tensor2d(X));

  const y = tf.tensor(toCategorical(data, "Churn"));

  const splitIdx = parseInt((1 - testSize) * data.length, 10);

  const [xTrain, xTest] = tf.split(X_t, [splitIdx, data.length - splitIdx]);
  const [yTrain, yTest] = tf.split(y, [splitIdx, data.length - splitIdx]);

  return [xTrain, xTest, yTrain, yTest];
};
```

Figure. 2: Code snippets for initial data processing and tensor creation

We created a two-dimensional tensor from our functions (categorical and numeric) and performed normalization. Then we broke the data down into training and testing datasets. The missing values were encoded as 0. The resulting deep neural network has two hidden layers with 32 and 64 neurons, respectively. It is Fully Connected Linear Neural Network. Each layer has a ReLU activation function [5]:

$$f(x) = x^{+} = max(0, x), \quad (2)$$

where x - neuron input.

This function is defined as the positive part of the argument. This allows for better data preparation for deep networks compared to the logistic Sigmoid and hyperbolic tangent function.

The model was trained using the Adam optimizer [31, 32], and the binary crossentropy function was used to measure the error [10]. The model learns for the first ten epochs, after which it reaches a plateau(fig. 3).

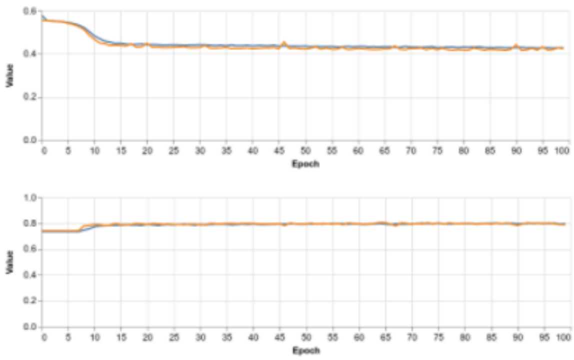

Figure 3: Visualization of model training up to 100 epochs

The model has an accuracy of 79.2% according to test data (based on the results of checking 10% of mixed data).

As a result (see Table 1), we found that linear regression, logistic regression, and Bayesian classifier have a low but stable evaluation quality. The decision tree and the reference vector method were forced to retrain, having a 100% result in the training sample, but a very low result in the test sample [30].

The optimal result was shown by using a random forest. This model has a stable and high evaluation quality. But it is quite expensive to implement in the IT infrastructure.

Table 1

Results of comparative analysis of machine learning methods for predicting customer churn

Method	Training sample	Test sample
Linear regression	0.76	0.75
Logistic regression	0.73	0.71
Neural networks	0.85	0.82
Decision tree	1.00	0.76
Random forest	0.88	0.87
Reference vector method	1.00	0.63
Naive Bayesian classifier	0.71	0.69

The principle of random lea prediction is that each tree in a random forest returns a class forecast. Trees have a very weak correlation between themselves. As a result, the class with the most votes becomes the forecast of the forest.

The forest is resistant to noise signs, and therefore the validation curve for the number of initial signs involved will reach the asymptote. That is, if the initial features are, say, 150, you can evaluate the importance of the features, build validation curves for models trained on 50, 60, .. 150 features and catch the moment when adding new, less important features does not improve the quality so much. The tree is built, as a rule, until the selection is exhausted (until only representatives of one class remain in the leaves), but in modern implementations there are parameters that limit the height of the tree, the number of objects in the leaves and the number of objects in the subsample at which splitting is performed.

On the other hand, such an analysis applies to large companies that have a heterogeneous package of services and large capital. From our point of view, among the methods considered, we should also analyze the approach to comparing machine learning methods used in similar businesses operating on the SaaS model, but in the field of B2B [14].

The dataset includes information about:

- Customers who disabled their subscription during the last quarter of Churn
- Services that each client subscribes to
- Customer account information-how long they have been a customer, contract, payment method, monthly payments and total expenses.

Decision trees are very sensitive to data. For this reason, we made small changes in the data set on which the model was trained. This led to significantly different tree structures. We used this advantage by allowing each individual tree to arbitrarily select data with replacement, which led to different trees.

The concept of a training sample is a key one in pattern recognition. A training sample is an independent sample $\boldsymbol{D} = \{\boldsymbol{x_i}, \boldsymbol{y_i}\}_{\boldsymbol{i=1}}^{\boldsymbol{l}}$ rom some distribution $P(x, y) = P(x)P(y|x)$. Here x_i , $i = 1, 2, \ldots,$ l — are feature vectors (called precedents), whose coordinates represent the values of n features (independent variables) measured on some object [10].

The corresponding y_i represent the values of the dependent variable. If y_i can take only a finite number of values, i.e. $y_i \in \{\omega_1, \omega_2, \ldots, \omega_c\}$, $c > 2$, then we have a classification problem. In this case, y_i is called a class label and determines whether the corresponding k object belongs to one of the c lasses, and the attribute itself is called class; if y_i is measured on a numerical scale, then we have a regression problem; in this case, the attribute is called a response; A decision tree [31] is a tree with each vertex t are associated: 1. the entire image space of $\chi_t \subset \chi$; is associated with the root vertex χ. A subsample $D_t \subset D$ of the training sample D, such that $D_t = \{(x, y) \in D : x \in X_t\};$ thus, the entire sample D is associated with the root vertex. Some function (rule) $f_t : \chi \rightarrow \{0, 1, \ldots, k_t - 1\}$ *(here* $k_t > 2$ — is the number of descendants of vertex t), which determines the partition of the set χ into k disjoint subsets. No function is associated with terminal vertices.

Let's denote $t_{i(t)}$, $i = 0, 1, \ldots, k_t - 1$ he vertex that is the i–th descendants of vertex t. Subset χ_t and rool f_t defines subsets $\chi_{ti}(t)$ as follows [5]:

$$\chi_{t_{i(t)}} = \chi_t \cap \{x \in \chi : f_t(x) = i\}, \tag{3}$$

The purpose of constructing a decision tree is to classify vectors x from a distribution $P(x)$.

In general, the reduction of pollution is defined as [32]

$$\Delta i_B(t) = \frac{\Delta i(t)}{-\sum_{k=1}^{B} P_k \, log_2 \, P_k}, \tag{4}$$

where B — the number of descendants of the vertex t, P_k — percentage of subsample examples $D(t)$, corresponding to the vertex t_k and $\sum_{\boldsymbol{k=1}}^{\boldsymbol{B}} \boldsymbol{P_k} = \boldsymbol{1}$. And the splitting that maximizes the value is chosen $\Delta i_B(t)$.

In the original dataset, we have 7,044 examples of B2B SaaS subscriptions and 21 variables (characteristics of companies that purchase services using the SaaS method).We have a very unbalanced data set. About 20% of customers are businesses that have been around for less than 3 years, and they are much more likely to have an outflow of customers compared to a long-term business. Answering the question of how long customers stay in the company, at first glance it seems that the longer the company remains a customer, the more likely it is that it will continue to be loyal in the future. But this is only visually and at first glance.

When building the model, we took into account the features of the model. The more trees, the better the quality, but the setup time and operation of a random forest also increase proportionally. To speed up the construction, n_jobs=-1 was used (build on the maximum possible number of processors). To construct reproducible experiments, a preset of a pseudorandom number generator was used: random_state [29].

4. Results

As the number of n_estimators trees increases, the quality in the training sample increases, and the quality in the test reaches the asymptote (Fig.4). According to the schedule, it was decided to build about 40 trees. The model was built at full depth, since the data is mostly not noisy.

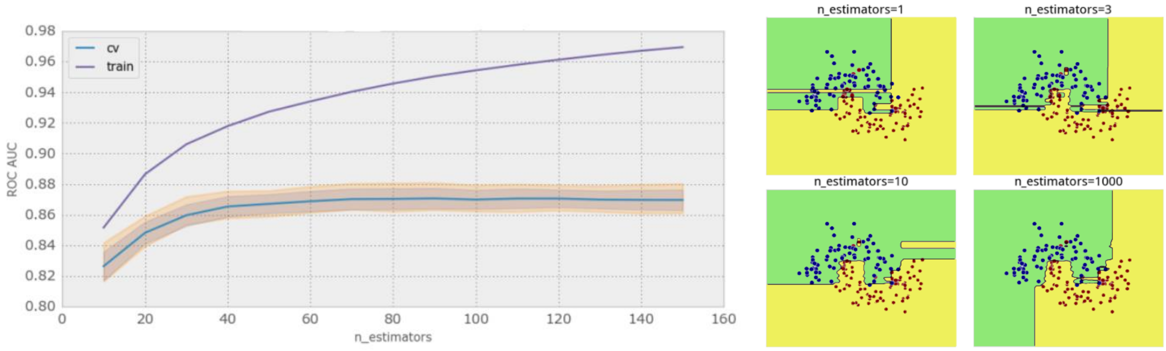

Figure 4: Quality when varying the value of the number of trees n_estimators

Having determined a sufficient number of trees in the forest, the number of features was selected for the choice of splitting. The quality graph on the test is unimodal from the value of this parameter, it strictly increases during training. When max_features increases, the time for building the forest increases, and the trees become "more monotonous".

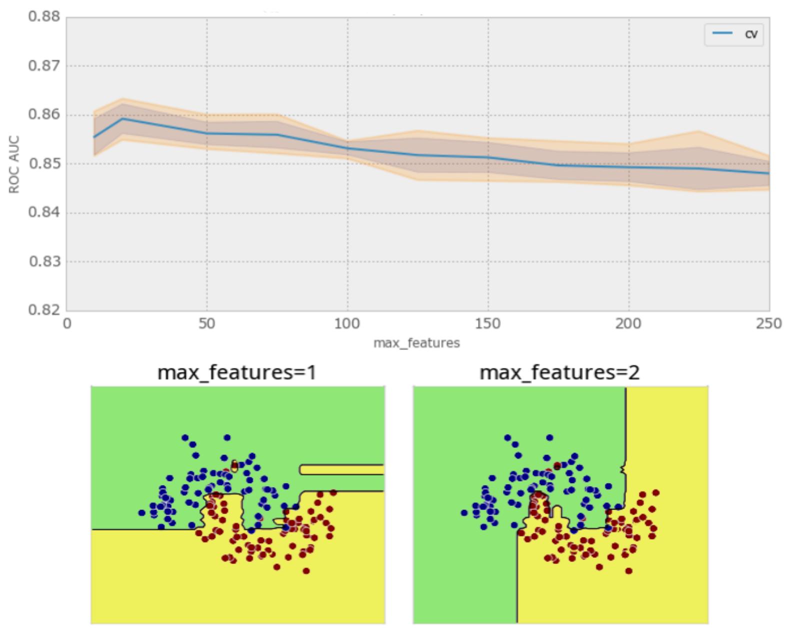

Figure 5: Quality when varying the value of the number of features for the choice of splitting max_features

Obviously, buyers with low monthly payments (<$230). Most likely, they will remain customers. However, the higher the total amount charged by the company, the higher the probability of retaining that customer.

The expected value of the expected outflow from each forecast in relation to total income is the same. Therefore, it is important for an IT company to understand what scale of customer inflow implies the projected volume of outflow.

The reason why the random forest model works so well is that a large number of relatively uncorrelated trees working together will outperform any of their individual components.

The key factor is the weak correlation between the trees. Due to this, just as assumed financial investments with low correlations (for example, investments in stocks and bonds) are combined to form a portfolio larger than the sum of its parts,uncorrelated models can predict more accurately than any of the individual forecasts. The reason for this effect is that trees protect each other from their individual mistakes until they constantly make mistakes in the same direction.

5. Conclusion

The paper analyzes modern models and methods for predicting customer churn using machine learning, which can be applied to B2B Software by Subscription of IT companies. Among them, the random forest method is highlighted and a separate analysis of the deep neural network method is performed. The latter is due to the fact that this method is widely used in the field of B2C telecommunications. the industry experience turned out to be acceptable for a different audience of consumers. A deep neural network with 32 hidden layers has shown fairly stable accuracy and allows you to identify the main indicators of early customer outflow signals. This will help it founders and their teams implement customer retention policies in advance through various marketing activities and additional services.

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