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Deep Convolutional Neural Networks for Customer Churn Prediction Analysis

Alae Chouiekh, Laboratory of Multimedia, Signal and Communications Systems, National Institute of Posts and Telecommunications, Rabat, Morocco

El Hassane Ibn El Haj, Laboratory of Multimedia, Signal and Communications Systems, National Institute of Posts and Telecommunications, Rabat, Morocco

ABSTRACT

Several machine learning models have been proposed to address customer churn problems. In this work, the authors used a novel method by applying deep convolutional neural networks on a labeled dataset of 18,000 prepaid subscribers to classify/identify customer churn. The learning technique was based on call detail records (CDR) describing customers activity during two-month traffic from a real telecommunication provider. The authors use this method to identify new business use case by considering each subscriber as a single input image describing the churning state. Different experiments were performed to evaluate the performance of the method. The authors found that deep convolutional neural networks (DCNN) outperformed other traditional machine learning algorithms (support vector machines, random forest, and gradient boosting classifier) with F1 score of 91%. Thus, the use of this approach can reduce the cost related to customer loss and fits better the churn prediction business use case.

KEYWORDS

Churn Prediction, ConvNets, DCNN, Deep Learning, Machine Learning, Telecommunications

1. INTRODUCTION

During the last decade competition became a real concern for telecommunication providers (Bin et al., 2007). Thus, operators are poised to find new methods to enhance the quality of their services and diversify periodically their portfolio to retain the existing customers and attract new ones. While the primary focus of each telecom service provider is to provide customer service satisfaction, preventing subscribers from churning remains a huge challenge. Churn in telecoms is the term used to collectively describe the ceasing of customer subscriptions to a service (Huang et al., 2010), and if one customer cancels his/her service and switches to another operator, this customer is considered as a churner. Converging lines of evidence showed that the cost for customer acquisition is much greater than the cost of customer retention (in some cases~20 times more expensive) (Vafeidis et al., 2015). Thus, it is compulsory to telecom service providers to identify unsatisfied subscribers to prevent them from churning. For this, developing reliable predictive models to predict customer churn are crucial for the business management of the telecom industry.

Telecommunication companies consider customer churn a real and serious common business problems that should be addressed very carefully to avoid the loss of potential subscribers. In our work, we focused on the prepaid subscribers, a category of customers who can terminate their service subscriptions and switch to another telecom provider without prior notice. For instance, we found

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that, in one major telecom operator in Morocco, the churn rate of prepaid subscribers is significantly higher than postpaid subscribers (Figure 1). While it is possible that such high churn rate in prepaid subscribers may be is due to factors related to high cost offer, low quality of the service, and/or high customer service dissatisfaction, being able to analyze and monitor customer behavior in time gives companies the opportunity to execute preventive measures for retaining them.

Several algorithms have been developed (Vafeidis et al., 2015), however it is not clear which of those models better fit for detecting the churning customers. To evaluate better the churning impact on customer's network, several experiments have been conducted using the state-of-the-art machine learning techniques with special emphasis on deep learning algorithms and convolution neural networks.

ConvNets (CNN) have been proved to have a very good performance in different area of research, including images and video recognitions (Simonyan et al., 2014; Yang et al., 2015; Hatami et al., 2018), natural language processing (Zhang et al., 2015), and speech recognition (Noda et al., 2015) by extracting high-level features from a large set of data. In addition, CNN has been demonstrated to have a very good performance in image processing tasks (Szegedy et al., 2015; Russakovsky et al., 2015). Thus, it would be of interest to use this technique to predict the customer churn by analysing images of represented customer's behavior.

Previous studies have shown that different state of art predictive models were used to predict the churning problem by (training binary classifiers) using labeled churner/non churner dataset involving the Traditional hand-crafted features (Keramati et al., 2014; Vafeiadis et al., 2015; The Chartered Institute of Marketing, 2010) or social network analysis technique (Phadke et al., 2013; Richter et al., 2010).However, motivated by the recent advances of deep learning (LeCun et al., 2015) in different area of research, we propose a novel method using convolutional neural network for customer's churn use case. Our method explores the efficiency of deep ConvNets for the predicting task, using the same structure of dataset handled previously by the-state of the art machine learning models (Keramati et al., 2014; Owczarczuk, 2010; Vafeidis et al., 2015; Kisioglu et al., 2011). More specifically, we focused on customer's behavior, which is represented as an input image describing calls/SMS/Data and a recharge temporal usage during two-month customer behavior. We found that ConvNets provides more meaningful and useful representations (yielded to optimal results), outperforming other conventional machine learning algorithms such as Naïve Random Forest, Gradient Boosting Classifier, and Support Vector Machine. This result indicates that our approach represents an important contribution to one open industrial question: how deep learning can be a useful method in addressing issues related to business telco data?

Figure 1. Churn rate comparison during 12 months