Machine Learning for Classification of IT Support Tickets

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***Abstract*—The IT support teams are responsible for the correct functioning of IT resources, ensuring that people can work with the least amount of interruption or struggle. The first challenge of the help desk team is to associate a support request with its correct topic, minimizing the ticket resolution time and increasing user satisfaction. This paper presents a machine learning classification model to identify the topic of the incoming support ticket. Our model achieves 75% of average precision among 7 categories. The complete code, model, and anonymized data to reproduce this work were made available online. A web prototype (backend and frontend) was developed for IT analysts to use the system in their daily work.**

***Index Terms*—Deep Learning, Text Classification, Natural Language Processing, Neural Networks, IT Support Tickets, Automatic Ticket Classification**

I. Introduction

Information Technologies (IT) are an integral part of our daily lives, and we are highly dependent on them for educational, social and professional purposes [1]. It is expected that those technologies "simply work", without interruption nor major struggles, so problems with them lead to great disruptions in our routines [2].

Within business and institutional environments, the IT support teams are responsible for the right functioning of IT resources [3]. When any user faces some issue regarding the IT resources, such as software packages, networks, or databases, he usually files a request in a management system known as a ticketing system. There his problem is described and registered. The next step is taken by the IT Analyst, that will handle the reported problem. All the actions taken to solve the problem are also reported inside the ticketing software [4].

The first challenge of the help desk team is to associate a support request with its correct service from the start [5]. The ticket subject has to be forwarded to an IT analyst to clarify the problem or understand the resolution. The analyst with greater expertise on the ticket topic should be selected to minimize ticket resolution time and increase user satisfaction. This will only occur if the ticket subject classification succeeds in identifying the problem correctly.

This paper presents a ticket classification machine learning model to identify the topic of the incoming support ticket, effectively helping IT teams to forward the ticket to the most suitable IT analyst. The contributions of this paper are twofold: first, a trained model for multilingual tickets classification together with the python code for its execution, available online in [6]; second, an open anonymized dataset with 2229 classified tickets, also available online in [6].

The following parts of this paper are organized as follows. A review of related works is presented in Section II. Section III describes the problem at hand and the solution applied to it. Section IV analyzes the results, and the conclusion and future research avenues are stated in Section V.

II. Related Works

There are several works involving the analysis, design, and implementation of ticket classification using different machine learning techniques. Authors in [3] worked with 1254 technical support tickets dataset for classifying 13 classes. The J48, decision table, NaiveBayes, and SMO (SVM-based) algorithms were used, with SMO outperforming the other techniques (prediction accuracy of 69.9%).

7 used a dataset from Google News with about 1.6 million support tickets and 32 ticket categories. Their model achieved an accuracy of 92% using SVM classifier and 91% using Logistic Regression, working with Term Frequency Inverse Document Frequency (TFIDF) bag-of-words.

Also, several companies develop classification solutions for their help desk management system. Uber Technologies [8] shows a deep learning solution (COTA v2) based on a novel Encoder-Combiner-Decoder architecture that combines text, categorical, numerical, and binary features from Uber's historical customer support data. It is applied as input features the ticket message, ticket metadata, user-level information, and trip-level information. On average, the proposed system reduced ticket handling time by about 10%, compared to their previous system.

Moreover, machine learning techniques can be used to identify similarities in tickets [9] thus saving a lot of time by giving IT analysts access to past remedial actions for similar kinds of issues raised earlier based on historical data. 10 presents a deep neural network (DNN) to measure similarity amongst tickets. In their solution, ticket summaries are preprocessed and represented by TFIDF feature vectors. The proposed DNN architecture resulted in a similarity match of about 70% to 90% between the model suggestions and the ground truth evaluation.

III. Proposed Solution

We used a dataset from an IT support company in the Florianópolis region, which contained 2229 support tickets manually classified into 7 categories (Table II). Each ticket is represented by an unstructured text field, which is typed by the user that opened the call. The classification process was performed in 2020 by three IT support professionals. The corpus contains tickets in many languages, mainly English, German, Portuguese and Spanish. Table I show 3 typical tickets and their classification.

TABLE I
Examples of typical support tickets

Text	Category
[TICKET ID] - New Support Ticket received Outlook Calendar not viewable	O365
reserva DHCP - Poderia fazer uma reserva no DHCP? MAC [MAC_ADDRESS] é uma impressora.	Support general
[TICKET ID] - Configure Windows account and additional services for [NAME] ([COMPANY]; RSNO) (Order Request ID [TICKET ID])	Active Directory

Before the data is made available for publication, all Personal Identifiable Information (PII) and sensitive information were removed (substituted by a tag indicating the original content, for instance: the sentence ”this text was written by Leonardo” is converted to ”this text was written by [NAME]”). The removal was performed in three steps: first, the automated machine learning-based tool AWS Comprehend PII Removal was used; then, a sequence of custom regular expressions was applied; last, the entire corpus was manually verified.

TABLE II
Distribution of tickets by category

Category	Percentual of tickets
Fileservice	34.7%
Support general	34.4%
Software	10.4%
O365	8.07%
Active Directory	5.34%
Computer-Services	4.13%
End of Life	2.86%

A fully connected neural network [11], with 500 input neurons (one for each of the 500 most common words in the training set), 4 hidden layers with ReLu activation function and dropout of 30%, and 7 output neurons with softmax activation function [12], was used as the classification model. The training was performed with batch size 32, for 100 epochs. The network was implemented using the Python programming language and the Tensorflow framework.

The quality of the model was evaluated using the Cross Validation technique, reserving 30% of the data for testing. From the training set, a further 10% was set aside for validation (follow-up during training). The metrics of precision and recall were then measured.

IV. Results and Discussion

Throughout the training process, it is observed that the accuracy converges to approximately 80% on the validation set after only 20 epochs (Fig. 1). There is also a considerable difference in accuracy between the training and validation sets, indicating that it may be possible to improve the results by using neural network regularization techniques and by reprocessing the data.

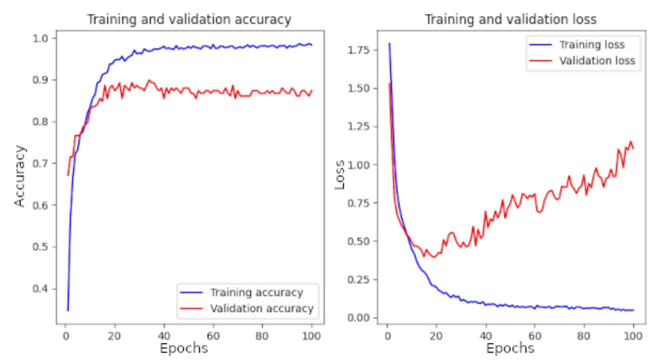

Fig. 1. Neural Network training process.

The calculation of the precision and revocation metrics, individually for each category, can be seen in Table III. It can be noticeable that in some categories the model result was more satisfactory. This difference seems to be more related to the intrinsic characteristics of each subject than to the number of tickets available for each category: the End of Life calls, for example, are automatically generated and have a standardized text, so they are very easy to be classified. Considering all categories, the average precision, average recall, and accuracy were all 75%.

TABLE III
Precision and recall evaluated in the test set

Category	Precision	Recall
Fileservice	92%	95%
Support general	75%	90%
Software	67%	53%
O365	82%	73%
Active Directory	41%	35%
Computer-Services	71%	41%
End of Life	100%	100%

The results were also summarized in the Confusion Matrix presented in Fig. 2, that compares the actual predictions versus the actual predictions. It is observable that some categories are more commonly confused with the ”Support General” category, for instance: 16.3% of the ticket from category O365 are misclassified as Support General. One possible explanation is that this category represents a wide range of situations, and is often used by support analysts to indicate that a call does not fit into the other categories.

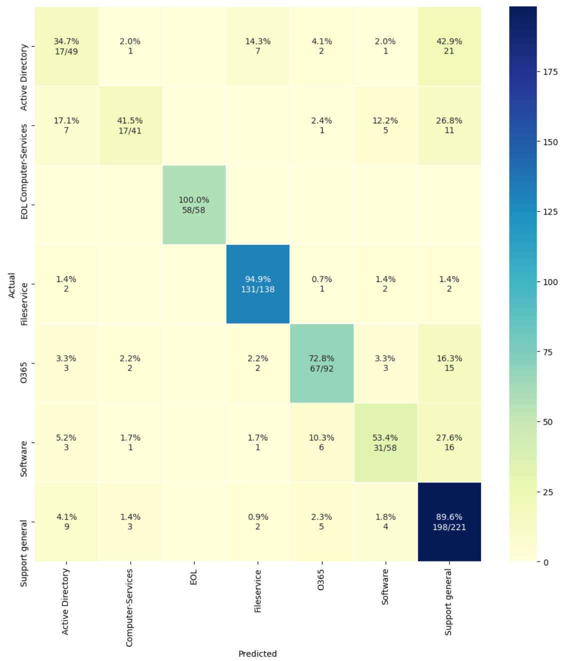

Fig. 2. Confusion Matrix evaluated in the test set.

To better evaluate the usefulness of the proposed system, a small web prototype was developed. The system exposes an Application Programming Interface (API) to perform the basic functionalities of the prototype: authenticate users, register new users, submit support tickets, among others. The web software was implemented using the framework FastAPI, commonly used for web systems development. Python was utilized as programming language, together with a Postgres database to store the tickets and user information.

To allow a graphical access to the application, a frontend was created using the framework VueJS and the programming language JavaScript (Fig. 3). Furthermore, the prototype integrates with both the main ticket management system and the messaging application used by the support team, in a way that the team receives a message immediatly after a new ticket is created (Fig. 4).

The system was deployed at Amazon Web Services, using the following cloud-native solutions: Amazon Relational Databases (RDS), Amazon Elastic Compute Cloud (EC2), and Amazon Elastic Block Store (EBS). Currently, the prototype is being used in the daily work of the support team of the company.

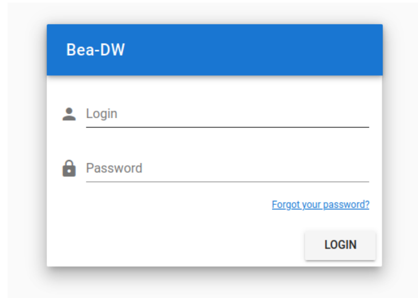

Fig. 3. Login page of the prototype.

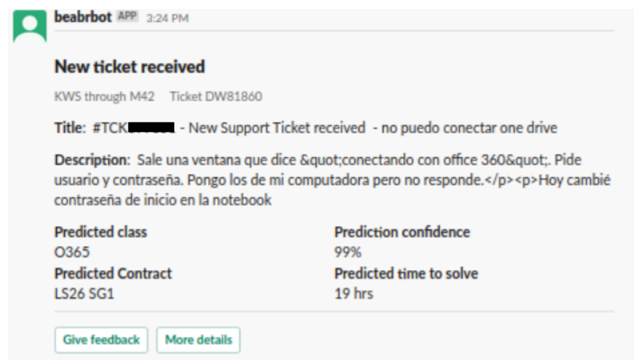

Fig. 4. message received by the team when a new ticket is created.

V. Conclusion and Future Works

Having high accuracy in automatic ticket classification is of crucial importance for support teams. A proper system can help IT analysts as it enables faster resolution of calls but, on the other hand, may cause the ticket to require manual forwarding or rerouting in case of misclassification. Therefore, it is crucial to test and compare other techniques that can be used to solve the problem.

The present work introduces a fully connected neural network for ticket classification. The average precision, average recall and accuracy achieved were all 75% for the seven categories in the 2229 support tickets used for training and testing. The category with highest precision was the End of Life, with 100% of precision, while the one with lowest precision was the Active Directory (41%). Additionally, the model was integrated into an application software that was used in the daily work of the support team of a company.

Ticket classification is not limited only for arranging by category. For future work, in order to facilitate the work of support analysts, there are other problems that can be automated or eased with the use of machine learning techniques: identifying the complexity level of the call, recognizing which technologies are being mentioned by the user and searching for past calls that can help the support analyst.

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