

Automating Customer Service – Improving Operations and Supporting Customers at Scale

The 4th-IR team designed a Machine Learning model to help the Customer Service Desk manage and prioritize customer issues by automating processes and leveraging corporate knowledge to provide a better customer experience. Leveraging historical data, the Machine Learning model was used to predict the resolution of new tickets, reducing turnaround times, standardizing processes and enhancing the customer experience.

Company Info:

Name: Customer Service Desk - European Financial Institution

Location: Europe

Industry: Banking

Challenge

The primary challenge identified by the 4th-IR team was the increasing volume of tickets from customers and the unstructured format of the requests. The complexity of business issues and the variety of sources and formats made it challenging to develop efficient and repeatable processes.

Dedicated teams were working round the clock to support and address each of the tickets correctly and swiftly. Ticket data was unstructured and the company was looking to automate human intensive tasks which involved reading and analyzing each ticket separately before responding, and sorting out the tickets to the right person or team. Customer requests were increasing while ‘time for resolution’ was escalating. The company was eager to automate customer service processes for their Customer Service Desk.

Solution

4th-IR’s team evaluated data from past tickets and processes to develop machine learning models that could be applied to achieve automated response suggestions. Machine learning models were developed using Similarity Analysis, Text Summarization, and Recommendation Engine. Ticket requests were summarized and customer service answers classified accordingly.

Results

- Increase of Corporate Knowledge Repository
- Reduced ‘Time for Resolution’ of customer requests
- Consistency and Accuracy
- Improved Customer Satisfaction
- Effective 1st Contact Resolution
- Improvement of the correlation between Cost per ticket / Time Allocation

Process

4th-IR began the project by analyzing the large volume of tickets in order to better understand the content and identify patterns or topics that were important. The team built an internal ticket explorer tool - a web app with a simple user interface which enabled them to query the data for specific terms. Another important step in the project was to clean and structure the data in order to transform it into a suitable state for use in building machine learning models. A pipeline of steps to refine and simplify the data was created and this involved separating and structuring response fields, which were often a combination of various different logs from different teams. Unnecessary fields were removed such as common greetings and closings, which provide no semantic use and would act as contaminants to the data source. Finally, the team stored a separate version of each text field with certain common words. This field was used in place of the raw sentences for certain models, when it could provide a benefit.

Category Classification

Once 4th-IR refined the data to a usable format, models were identified which could be used to extract useful insights from the ticket text data. The goal was to convert text data into numeric data, allowing the team to automate and analyze vast amounts of text using computational analysis.

A Category Classifier was built that could automatically identify which service category a ticket belongs to when given the text that the user submitted. Two different machine learning models were identified and implemented for comparison. Both models work by feeding in labeled data, which the model uses to iteratively learn from. It does this by rewiring itself in response to the mistakes that it makes on each sample of data that it sees, a process known as “training”.

Similarity Analysis

Another task performed by 4th-IR was to quantify the textual similarity between tickets. This can be used to identify relevant tickets which could be displayed to customer service representatives alongside the ticket they are working on. This provides valuable context for the Customer Service Desk representatives by showing them how similar tickets were handled, with the potential to reduce ticket processing time at scale.

The 4th-IR team implemented a variety of models, from simple to state-of-the-art, including bag-of-words, word embedding, and neural networks. A final assembled model was produced to average together all predictions from any given subset of models. In total, five unique models were identified which showed good performance on identifying semantic similarity.

Similar tickets were identified and responses were used to cluster them into distinct groups. This opened up the possibility to direct customer-service representatives to an automatically curated set of similar ticket groupings without showing them many different iterations on the same ticket.

Automated Question Answering

Using the knowledge database of the Customer Service Desk, automation was implemented for the answering of customer queries. 4th-IR used a multi-step process through which useful models were stacked together to create a data science pipeline. The first step of this pipeline is to identify, given a customer’s question, which paragraph in the knowledge database is most likely to contain an answer. Both the question as well as the relevant paragraph were inserted into a state-of-the-art neural network called ‘BERT’. This network is trained to look through the paragraph and output the answer to the particular question it is given. In the end, this allows a user to type in a question in natural language and get a response directly from the knowledge database.