Case Study: MLE Systems uses machine learning to help customer services deal with email overload

A large UK high street bank wanted to improve on their back-office email practice for their small business accounts. They had a team manually reading all incoming emails, deciding which department they should go to, and copy-pasting the text into a PEGA ticketing system, which was causing a backlog.

This was also a very expensive process as it required a large team of people to read each email before passing them on to be actioned by the right teams. And it all resulted in a poor customer experience, as customers had to wait a minimum of 2 days for a reply.

Once hyped as the ‘next big thing’, it is now being put into practice by a wide range of businesses to improve the effectiveness of email.

OBJECTIVES

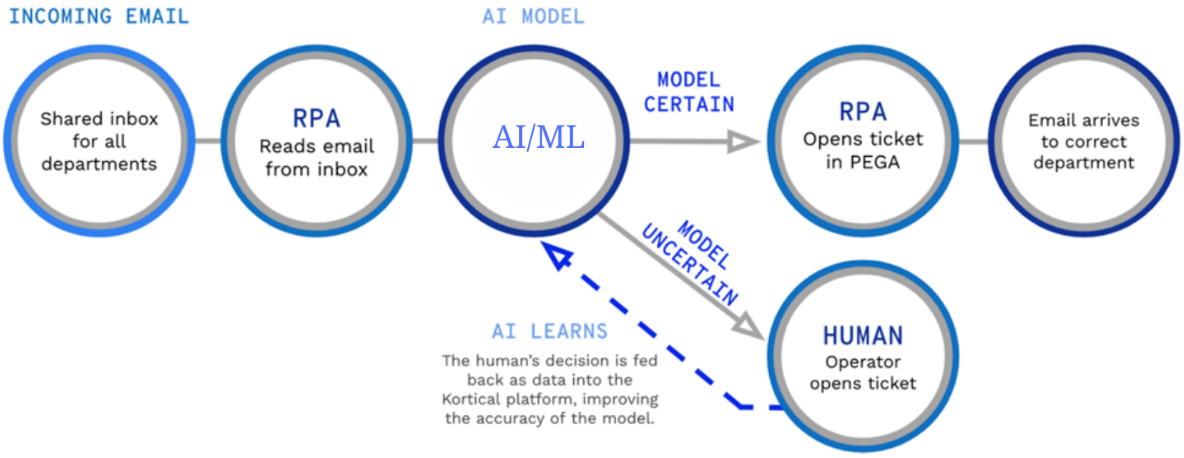
They wanted to see if advanced Natural Language Programming (NLP) techniques could automate the common queries, removing the need for people to read emails and to automatically send them to the right department.

The aim was to see how many could be automatically sent and how many needed more training data.

OUR APPROACH

Traditionally Data Science projects require thousands of labelled training sets. Still, in this case, as a high percentage of emails were fairly consistent we had a training set of fewer than 300 emails.
The training set consisted of customer emails and the department they went to.

Using the AutoML platform we could generate thousands of models and explain the models and how they understood the emails so that we could demonstrate how the models work and make intuitive business sense. We held back a portion of the data as a test set to prove the model's accuracy.



AT A GLANCE

This cutting edge email automation solution was delivered in 4 weeks vs a typical AI integration programme that takes 2 - 4 years*

AUTOML & RPA

Implementing AI into legacy systems can at times be expensive and a time consuming challenge, with a high potential for unknown unknowns to put project timelines at serious risk. We overcame this potentially costly exercise by using RPA to read the incoming emails and send them to bank.
Bank then interprets the email and provides the correct destination, which is sent back to the RPA. This in turn is then put into the ticketing software by the RPA. The combination of bank AI as a Service & RPA speeds up the integration considerably and allows the rapid adoption of an automated solution with minimal upfront time and cost.

THE RESULTS

In 4 weeks we were able to deliver really exciting results against the key objectives:

- Bank developed a Machine Learning model that could process 57% of the emails with a 95% accuracy
- This gets smarter over time as there is more training data generated from every new interaction