

AI Solutions in the Banking Environment



Artificial intelligence, or AI for short, is currently on everyone's lips. We associate buzzwords such as machine learning, neural networks and self-learning algorithms with a modern trend technology that we already encounter all too often in everyday life: Be it voice assistants like Alexa, Siri, Cortana & Co, personalised advertising while surfing the internet, traffic jam reports from Google Maps or sense-based translation tools like DeepL.

But what about the use of AI solutions in the banking environment?

In this number-based world there are naturally many interrelated ratios to calculate, optimise and predict, so that one could think that the use of AI-based tools should be obvious here. All the more surprising for us was the insight that many of our customers do not yet rely on AI support in the execution of their banking transactions. So, there is huge potential in this environment that is just crying out to be exploited.

For this reason, we at FERNBACH have been thinking about this topic.

True to the motto:

'AI will probably most likely lead to the end of the world, but in the meantime, there'll be great companies' by Sam Altman, CEO of the non-profit organisation OpenAI, which is funded by none other than Microsoft, Amazon and Elon Musk.

The result is an AI solution using neural networks that can be flexibly applied in various lines of business within a bank, for example as an early warning system for non-performing loans by predicting future default days or probabilities, or as a decision support tool when making new loan offers to customers.

Of course, we are aware that the use of AI-based tools for banks in the area of regulatory reporting does not seem to be particularly easy at first glance, as auditors and reporting authorities could argue with some degree of justification that, for example, the traceability of the calculation of predicted probabilities of default using neural networks is not given. At least not in the way we are familiar with classical statistical methods such as linear regression analysis. In fact, however, the FSB itself published an article back in November 2017 ('Artificial intelligence and machine learning in financial services'), from which it emerges that the use of AI-supported systems on the part of both banks and reporting authorities is not only permitted, but even expressly desired. We, too, assume that regulatory reporting will not be able to avoid AI-driven algorithms in the future - simply for the reason that the results obtained with them are more precise and thus reflect reality more realistically.

As Ginni Rometty, CEO and president of IBM, has put it, 'Some people call this artificial intelligence, but the reality is this technology will enhance us. So instead of artificial intelligence, I think we'll augment our intelligence.'

Those of you who have read this far may now be wondering what we at FERNBACH have actually done and developed. Let's take a closer look at our AI-based early warning system for non-performing loans and payments, which uses a neural network to predict the number of future days of default:

1. What was our incentive and what goal did we have in mind?

We believe that the final default of payments could often be avoided by an early introduction of measures that are focused on the individual customer situation and thus the risk of default could be significantly minimised. Therefore, the goal of the project was to forecast the number of days past due for regular payments (such as installment payments for loans or subscription fees). With this in mind, we developed a procedure that can be used to predict the future payment behaviour of customers in arrears at an early stage.

2. What methodology is used?

We use a so-called recurrent neural network. In contrast to conventional feed-forward networks, recurrent networks can take into account the temporal order of the input data. Thus, the number of days past due of a transaction at booking day t is also used as another input parameter for the calculation of days of default at booking day $t+1$.

3. Which data basis is needed?

Every neural network needs a data pool as a basis. This pool is used to train the network. Basically, it can be said that data of any structure can be used for training. Once trained, new computational results can be obtained in seconds. Just as in Muhammad Ali's wheelhouse, who once said, *'I hated every minute of training, but I said: Don't quit. Suffer now and live the rest of your life as a champion.'* The data pool required for our AI-based forecasting tool consists of the following three components, which are usually available to every bank in their databases: historical business data (payment history, days of default in the past), customer DNA (personal and economic characteristics of the customer such as age, annual income, debt burden, occupation, nationality, marital status, etc.), and values of macroeconomic parameters (e.g. inflation rate, oil price, GDP).

4. What results were obtained and how meaningful are they?

During the development of our AI solution, the data basis consisted of an original database of a bank over a period of seven years, whereby the database was available to us at the end of each month. The data basis was all payments that were in arrears (including the corresponding number of days past due), all payments that were not delayed, as well as customer DNA and values of certain macroeconomic parameters. A recurrent neural network was created and fitted with 84 months of raw data. The last three months were not used for training, but rather for a backtesting, in which the actual default was compared to the calculated one. It turned out that our developed neural network clearly beats conventional forecasting methods such as the ARIMA model in all quality indicators such as accuracy, recall

AI Solutions in the Banking Environment



and precision.

5. What did we learn from this?

Banks do have a lot of data, but they do not always live up to the name of a databank in the literal sense of the word: Historical data sets exist in every bank, but the quality of this data is often worse than expected – there are gaps in the time series, some time series are obviously stored incorrectly (how can a deal jump from zero to 60 days past due within one month?) and there may not be much historical data. However, we have always achieved better results with less but consistent data. Loss databases, for example from the Basel context, are a suitable starting point for a data pool. Furthermore, the credibility of the obtained results necessarily must be confirmed by a backtesting procedure. In addition, neural networks should be fed with new historical data and retrained at regular intervals in order to constantly achieve a high degree of accuracy.

In summary, we can proudly claim to have developed a solid system of an AI solution in the banking environment by using neural networks. Based on the use cases described above, this system can be used flexibly in any bank. In our opinion, the biggest advantage of using neural networks, besides the good prediction quality, is that the input data can be available in any structure. Specifically, this means that the data to be used does not have to be linearly related, as is the case, for example, in IFRS 9 when linear regression models are used to calculate point-in-time probabilities of default. Indeed, this is a major advantage of using neural networks, since for the majority of real time series there is no linear relationship: or do you think, for example, that generally a customer's annual income is proportionally related to his probability of default?

Whatever the case, when it comes to AI, we at FERNBACH share the opinion of the former German Federal Minister for Research and Technology, Hans Matthöfer: *'Artificial intelligence is always preferable to natural stupidity'*. In this sense, we would be happy to support you in the future with our AI-based solutions in the banking environment.

About the author

After studying mathematics at the University of Trier, Dr. Andreas Jung completed his doctorate in the research area of "complex dynamics/hypercyclic operators" and has been a Stakeholder Risk at FERNBACH for several years, working mainly in the area of IFRS 9 (with a focus on ECL calculation using statistical methods) and regulatory reporting (Basel III, credit risk).

About FERNBACH

FERNBACH is a group of medium-sized companies operating worldwide in software solutions and consulting whose hallmark is many years of Fintech expertise combined with a strong customer focus.

Your contact

Austria

FERNBACH-Software GmbH
Millennium Tower, 38th floor
Handelskai 94-96
1200 Vienna
Tel.: +43 (0) 1 236131522
austria@fernbach.com

Germany

FERNBACH
Bethmannstraße 8
60311 Frankfurt/Main
Tel.: +49 (0) 34605 45022
germany@fernbach.com

Luxembourg

FERNBACH Financial Software S.A.
6c, rue Gabriel Lippmann
5365 Munsbach
Tel.: +352 40224422
luxembourg@fernbach.com

www.fernbach.com

info@fernbach.com