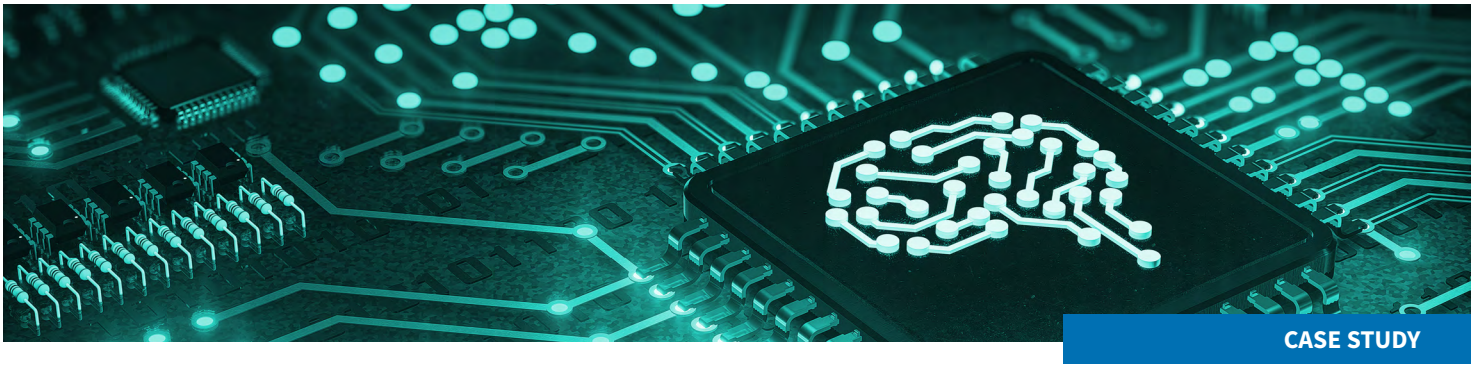

CASE STUDY

Are you using machine learning to improve Continuous Monitoring?

Find out how FTI used deep neural networks to identify improper payments with 99% accuracy

SITUATION

FTI Consulting was instructed to assist with an internal investigation which involved our Data & Analytics team building, training, and deploying an ensemble of deep learning neural networks (artificial intelligence) to identify potential improper payments and expenses.

OUR ROLE

We initially performed our investigations of potentially improper payments using a combination of manual processes and SQL scripts. A set of rules were defined to identify the improper payments/expenses based upon various data attributes and their respective correspondences or linkages across a procurement system (PS) and General Ledger (GL). If a correspondence or linkage between PS and GL could be established based upon the rules, the relevant row(s) in each dataset were flagged by us as linked (i.e. potentially improper).

After the initial investigation the team expanded the search to include machine learning techniques. We selected a highly powerful and complex nonlinear class of methods known as deep learning neural networks (or 'deep learning'). We opted for deep learning in this situation because it has the ability to faithfully replicate the work our analysts previously performed using manual processes and SQL scripts, but also much broader potential.

The aim was to fully automate the identification of improper payments moving forward and to establish a deep learning architecture which could be used on a wider range of transaction monitoring and fraud detection and enable a broad range of Continuous Monitoring.

We designed, built, trained, and implemented 3 different machine learning models in order to replicate the results obtained via manual processes and SQL scripts. We combined our AI models into an 'ensemble' to obtain better predictive performance. We trained our model on 64% of the labelled data so that it was able to replicate the matching rules and validated our model on 16% of the data, to test it. Finally, we ran a completely fresh test on an out of sample (or 'held back') subset of the data, which the model had previously never seen.

OUR IMPACT

Once trained, our model consistently replicated the rules with over 99% accuracy. It also predicted potentially improper items in new datasets with high precision.

To find out more please contact:

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