

SYNTHETIC DATA FOR DATA AUGMENTATION

# Augmenting historical financial data with synthetic time series

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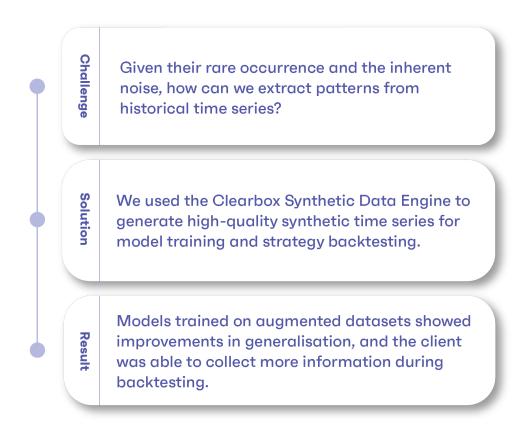


### Introduction

**Financial time series** are beneficial to **train machine learning models** deployed as trading agents, market indicators and forecasting tools.

Nevertheless, a few **issues** may appear: historical financial data presents itself with a high degree of **noise**, and forecast targets often represent **rare events**. For these reasons, models, especially deeplearning ones, tend to **overfit** and struggle at **generalising**.

This use case displays our work with a **financial trading company**, showing how **synthetic data** could effectively help **improve models** and that companies can also use it to enhance **strategy backtesting**.





## Challenge

Machine learning proved to be a valuable asset in the financial trading field due to the vast historical financial data available. Yet, a few critical issues still affect machine learning models: data often shows much aleatoric noise, and the design of many ML agents is to predict events characterised by very low occurrences.

Furthermore, markets keep changing due to small and large **scale events**. That's why models defined by many parameters such as deep learning architectures tend to **overfit**, i.e. they perform very well in terms of validation metrics, but they stop accurately working when presented with Out Of Sample test data. In addition, **backtesting models** over short time intervals provides limited information about the model behaviour.

# Solution

We helped the client solve this challenge through our Synthetic Data Engine, **generating multivariate synthetic time series** representing several financial instruments over time. We segmented the original data in an unsupervised way through the **data profiling and assessment tool** while determining **anomalies** and **outliers**. This information **facilitates the parametrisation** of the synthetic output, for example, by focusing on particular market trends.

We then used the Synthetic Data Engine to generate historical time series and create data points to **augment the supervised training process**. To obtain the augmented dataset, we assembled minority samples to **help with class imbalance issues** and **populated data segments** associated with low accuracy.



### Result

The process included the use of synthetic time series in two different areas. First, we used the **synthetic data to improve model training**, helping with target class imbalance and parametric regularisation. Second, we fed the same series to a market simulator to **generate additional backtesting output**.

The use case showed that **synthetic data helped improve model regularisation** - and thus **performance** - **for Out Of Sample points**, especially for imbalanced prediction targets. At the same time, extending the backtesting analysis to additional synthetic scenarios made **model behaviour analysis more comprehensive**. It made it possible to extract rule-based trading strategies from ML trading agents.

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