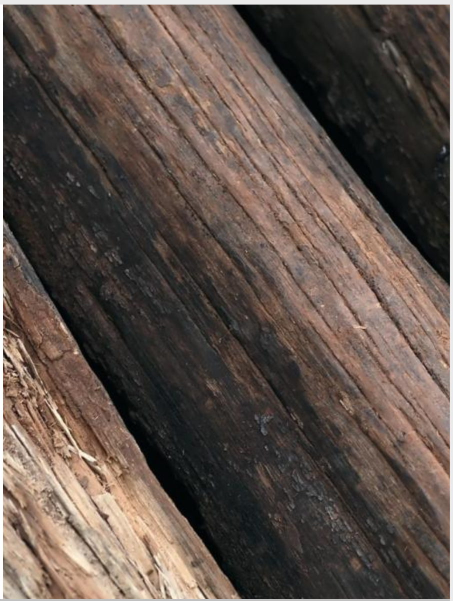
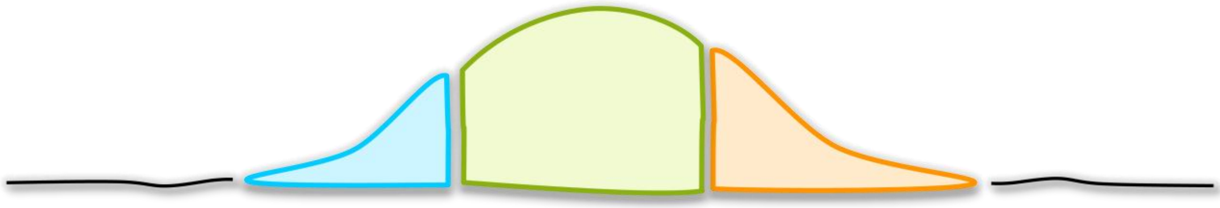


COMPANY REFERENCES

We provide a selection of project references of Python Predictions in the application of Predictive Analytics.

We link the majority of the applications to a specific phase of the customer lifecycle.

THE CUSTOMER LIFECYCLE



THE CUSTOMER LIFECYCLE: LEXICON

The typical lifecycle of a company's clients evolves through a number of distinct stages. Initially, the company possesses no information on the potential client, who is called a 'suspect'. Some potential clients, however, are known in the database, but have not purchased yet, and are called 'prospects'. After an initial purchase, most companies treat their 'new clients' differently for a well-defined period. Optimally, these customers evolve into 'active clients', exhibiting regular purchase behavior. Unfortunately, clients do not remain client forever, and some clients may be considered 'at risk'. When clients have stopped regular purchasing, they are considered 'inactive clients'.

PROSPECT

At eni Belgium (utilities, www.eni.be), new client recruitment suffered from a historical focus on acquiring low-profitable clients. Clients easy to convince were targeted first in door-to-door sales, but proved to be unprofitable later (due to high credit risk). By using predictive analysis, Python Predictions succeeded in defining segments of potential clients that were up to 7 times more profitable than undesired segments.

NEW CLIENT

At ING Belgium (financial services, www.ing.be), clients with a new relationship were targeted according to a business-rule based product sequence. A predictive model based on similarities between clients was constructed to replace the current system, and improved conversion rates on tested products by 25% to even 600%.

ACTIVE CLIENT

At Overtoom Belgium (B2B multichannel retail, www.overtoom.be), clients used to be selected for marketing campaigns through an RFM segmentation scheme. In their first application of predictive analytics, Overtoom gained 10% in revenue due to better definition of the optimal target groups. Additionally, by adapting the content of marketing campaigns towards every individual client, Python Predictions increased the relevance of the campaigns by 300%.

CLIENT AT RISK

At Mobistar Belgium (telecommunications, www.mobistar.be), customer defection – also called 'churn' – is a major issue due to the competitive environment. Since the existing predictive models were outdated, Python Predictions constructed two new churn models. In this way, Python Predictions succeeded by detecting 50% of all churners by only selecting the top 10% of clients with the highest expected churn rates.

INACTIVE CLIENT

At Overtoom Belgium (B2B multichannel retail, www.overtoom.be), Python Predictions created and implemented a system for early detection of inactivity. In first campaigns, the system proves very successful for detecting lapsed contacts, and is used to enhance the quality of the database.

BEYOND THE LIFECYCLE

CREDIT SCORING

At Unigro (catalogue retail, www.unigro.be), the vast majority of revenues are generated by the sales of items on credit. Hence, the decision to accept or refuse credit to applicants is of strategic importance. Since 2004, Python Predictions has been in charge of the development, maintenance and monitoring of the credit score models used in assessing creditworthiness.

SEGMENTATION AND PROFILING

At Makro Belgium (B2B and B2C retail, www.makro.be), marketing management requested a clear view on client profitability of its B2C clients. In 2011, Python Predictions constructed a segmentation scheme that clearly defined five distinct profitability segments, from unprofitable segments to top profit segments, in which a small proportion of clients represented a significant proportion of profits. Each segment was profiled in detail on dimensions such as demographics, store distance and typical purchase behavior (spending, visits, promo-usage, shopping basket content,...).

MODEL INDUSTRIALISATION

At ING Belgium (financial services, www.ing.be), since 2006, a large number of predictive models have been constructed to improve marketing results across all phases of the customer lifecycle. In order to maintain efficiency, the scoring of these models was automated since 2007 by Python Predictions, and ING staff was trained in the development and industrialization of new predictive models. In this way, only a limited amount of time is spent monthly to deploy all model outputs, and output quality is monitored automatically. In the second semester of 2011, the 35 available models jointly produced 250 million indications of product interest for its 2 million retail clients, of which only the top 1 million indications were recommended and forwarded to campaign management.

PYTHON PREDICTIONS

For additional information, please visit www.pythonpredictions.com