PERSONALIZED INCENTIVE RECOMMENDATIONS

USING ARTIFICIAL INTELLIGENCE TO OPTIMIZE YOUR INCENTIVE STRATEGY

CONTENTS

INTRODUCTION

The artificial intelligence (AI) revolution is upon us. Advanced machine-learning algorithms are being built into AI solutions to take on many of life's tedious and time-consuming tasks. Marketing is no exception.

A particularly innovative marketing application for AI leverages machine learning to produce personalized incentive recommendations. Advanced marketing technology can now utilize AI to deliver the best discount for each customer based on individual shopping history, browsing and buying behavior, and past engagement.

"We never knew if the discounts we sent were appropriate or not; were they too big, were they too small, were they even necessary? Managing discounts on an individual level was too time-consuming, and we couldn't tell who should get what."

Svetlana Novichkova, Head of E-commerce at Japan Centre

OPTIMIZING INCENTIVE RECOMMENDATIONS

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A recent survey conducted among Emarsys customers found that incentive strategies pose a common challenge for marketers, who struggle to understand which incentives should be sent to each contact to generate the most sales and maximize revenue.

Discounts, free shipping, buy-one-get-one offers, and other types of incentive work to entice customers to buy. However, marketers often don't have enough detailed information to decide which incentive will be most effective for each customer, or if a customer even requires an incentive at all. If used too liberally, incentives impact brand perception, and customers might even begin trying to game the system.

The Emarsys survey revealed the majority of marketers use general incentives for all customers. For example, all current, past, and potential customers are sent a 15% off coupon. The thought here is that even a one-size-fits-all incentive should perform better than no incentive at all. However, this is not necessarily the case, and can often lead to missed revenue as some consumers might not need any incentive at all to make a purchase. Alternatively, a different discount might have been the difference between a customer making a purchase and abandoning their cart.

The sheer volume of work that would be required to manually match an incentive to every customer is overwhelming. It's virtually impossible, not to mention incredibly inefficient. Thankfully for marketers, AI makes it possible to deliver personalized incentives to each customer quickly and easily.

"Individual incentive and voucher matching was never really a possibility. It was all or nothing on a campaign-wide basis. When it came to defining the nature and quantity of the incentives, it was a guessing game that tried to balance engagement gains with margin hits."

Russell Nicholls, Commerce Director at Evolution Slimming

DATA SCIENCE AND INCENTIVES: BUILDING AI INTO THE STRATEGY

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In a truly personalized incentive strategy, each customer receives the incentive most likely to convince them to make a purchase. This customized approach not only drives sales, but also improves the customer experience, thus strengthening the relationship between customer and brand.

The model referred to throughout the rest of this whitepaper is predicated on the simple aim that when an incentive, such as free shipping, is offered to a customer, it is expected to have a positive effect on the customer's potential to convert. In contrast, each incentive also carries an associated business cost once validated. For example, the expenditure the business incurs by offering free shipping. The goal of the incentive strategy is to maximize the expected benefit, balanced against the constraint of expected costs.

Artificial intelligence is able to identify insightful concepts and themes across large data sets, without any manual labor from marketers.

The expected benefit: Δp*c - where Δp is the increase in the chance of spending (often referred to as buying probability), and c is the amount of spending (cart value). We assume that the incentive exerts effect only through increased probability of buying, it does not influence the cart value. The expected cost: p*d - where d is the cost of incentive (for a 10% discount d = 0.1*c).

In the predictive model for the individual's buying probability (p) and cart value (c), there is an important piece of information missing: the effect different kinds of incentive (Δp) have on the equation. One might expect, for example, that larger discounts perform better, and that they will convert more customers who would otherwise be less likely to spend. However, this is not necessarily true. A stronger approach is to begin with predefined assumptions and then refine them by observing and measuring individual reactions. To build such an AI-based solution, a machine-learning algorithm should first be applied, with a proper mathematical predictive model to support it.

In the model showcased, the buying probability is predicted by using available spending history and email behavioral data. The calculation produces a number between 0 and 1 to express the likelihood a customer is going to buy in the next two weeks.

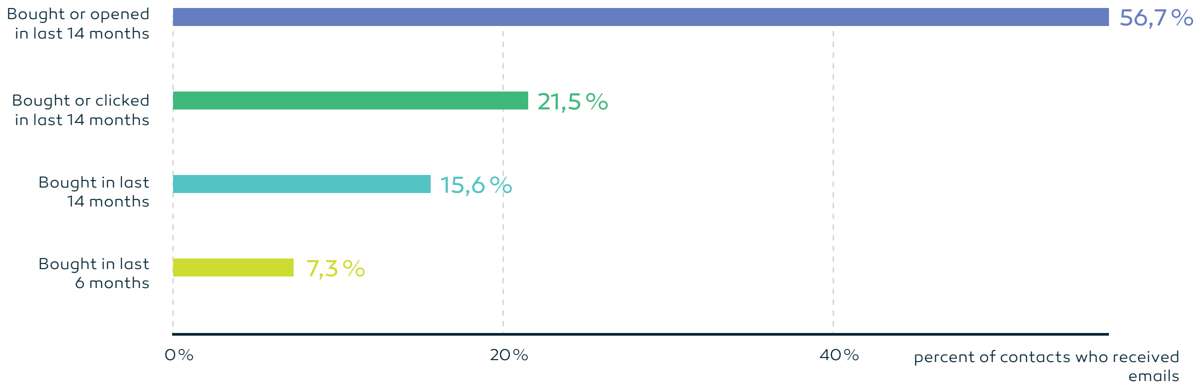
Following agile methodology, the model was created to strive for perfect balance between precision and complexity to maximize value while minimizing development efforts. For this reason, only individual purchase history was used initially. However, both the prediction's performance and coverage could be improved by including more data.

In general, most customers are not highly engaged. Therefore, using the last 6 months' purchase behavior data might not provide enough information (coverage) for most customers. However, if the date range was increased and email behavior data was also added, the model's coverage could be expanded to a larger customer group.

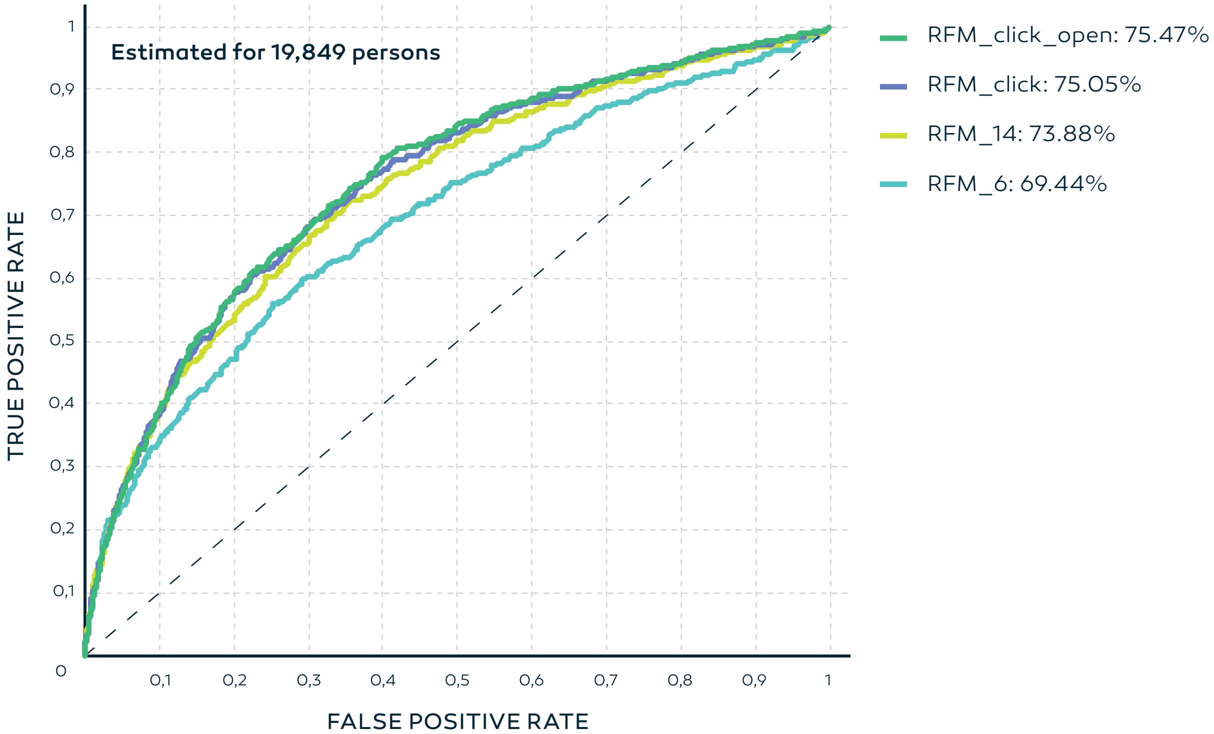
In the model, four different data ranges were tested:

- Purchase behavior data from the last six months.
- Purchase behavior data from the last 14 months.
- Purchase and click behavior data from the last 14 months.
- Purchase, click, and open behavior data from the last 14 months.

This is illustrated in the graph below, which shows the proportion of customers who received emails in the last 14 months and took some form of action in the observation period (and thus provided some personal data).



ROC curves are presented on the graphs below. These curves were used to evaluate the performance of binary predictive models (such as 'buy' or 'do not buy'). Each line corresponds to a specific version of the model, and the model is better if the area under the curve is larger. For perspective, a random guess would lie on the 45-degree line, achieving 50%.



Based on the above graph, it was decided to proceed using the RFM_click, rather than RFM_click_open, due to a tradeoff between the coverage and development efforts. The 'open' and web behavior data could be added later to improve the model's performance and coverage.

MODEL FOR BUYING PROBABILITY

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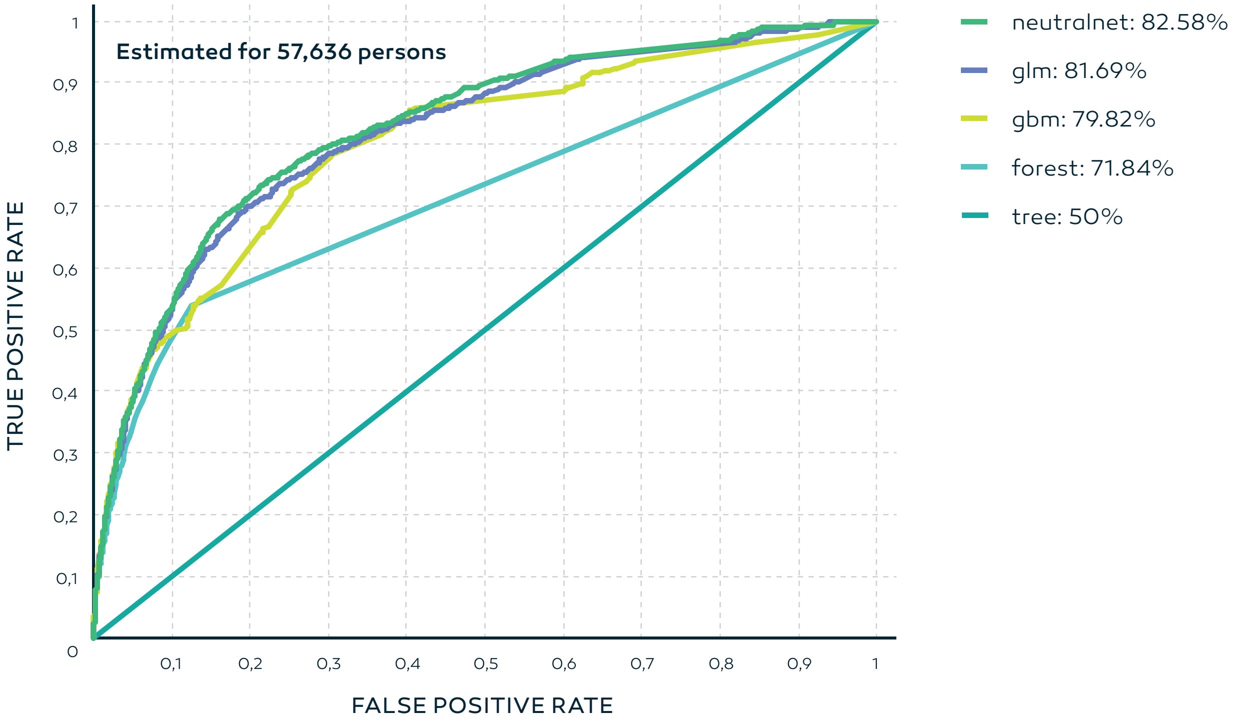
Once the data was selected for predicting buying probability, the next step was to select the prediction method. As it is used in the production system, it is important to find a balance between accuracy and computational effort. Therefore, the following models were compared: Logistic Regression, Decision Tree, Random Forest, General Boosted Trees, and Neural Network. Their performance is illustrated in the chart below.



The neural network model appeared to be the most accurate, but the model proceeds with logistic regression. Logistic regression allows for easy interpretation of the business' coefficients, and the computation effort is much lower. The final model included recency (R), frequency (F), monetary (M) values, the number of clicks (C) from the last 14 months on customer level, and finally, a binary variable (B), which considers one customer who did make a purchase in the investigated time period. Based on the feature variables, the likelihood that a customer will make a purchase in the next two weeks can be predicted.

The predicted buying probability of a customer is as follows:

$$p = \frac{1}{1 + e^{-(\beta_0 + \beta_1 \cdot C + \beta_2 \cdot R + \beta_3 \cdot F + \beta_4 \cdot M + \beta_5 \cdot D)}}$$

Where the β coefficients come from the model estimation.

PREDICTING CART VALUE

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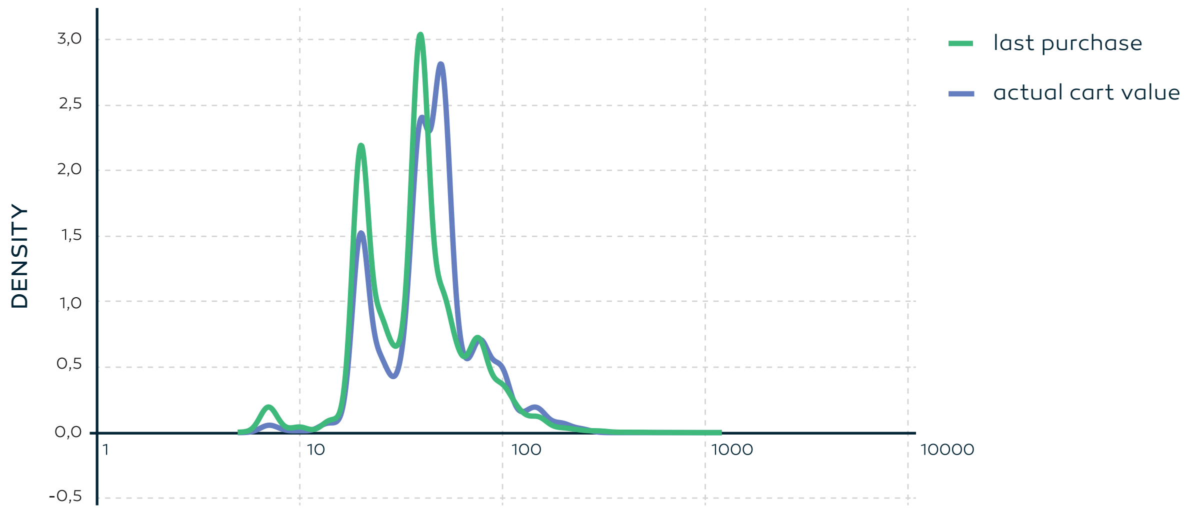
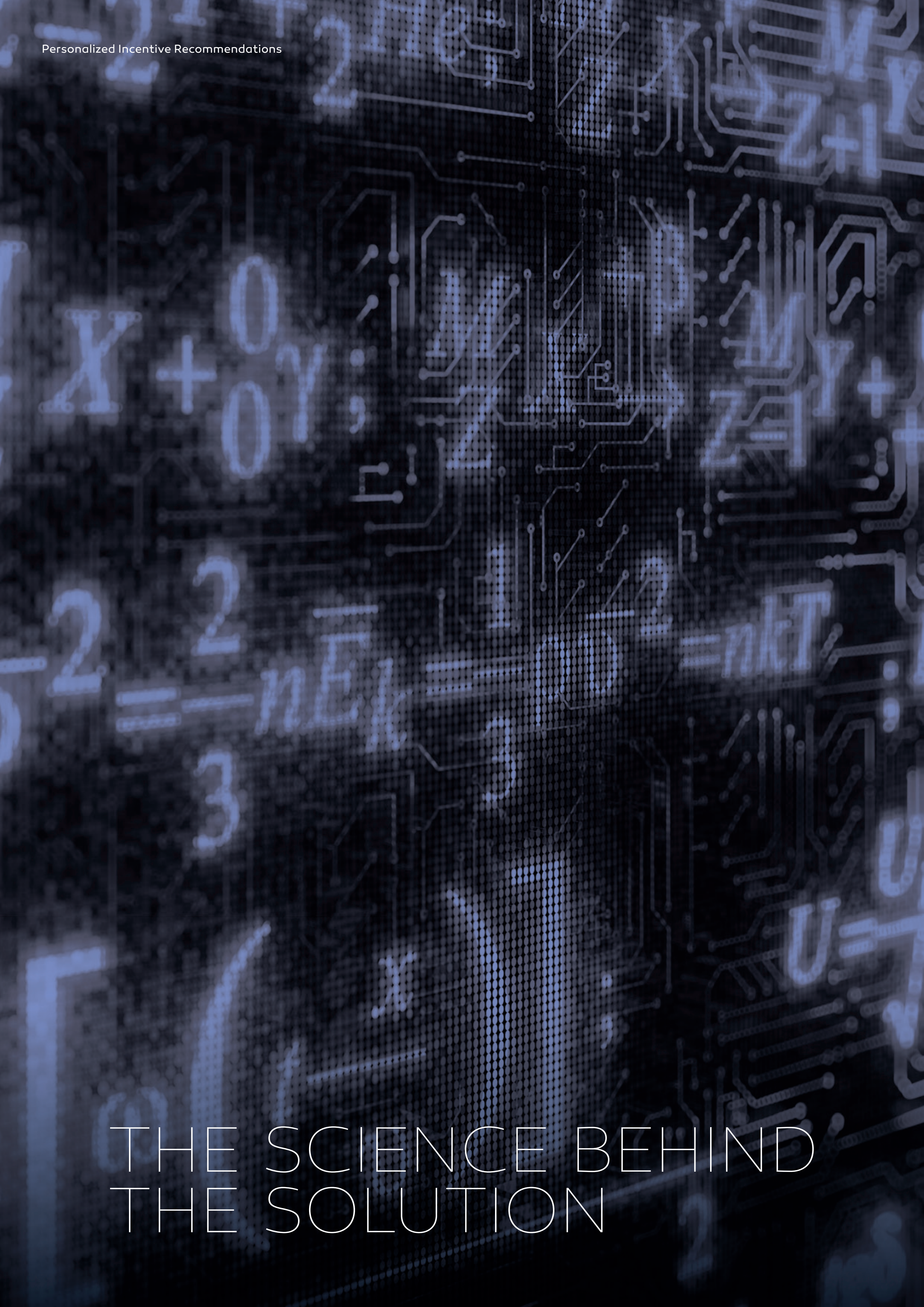
Cart value can be predicted using the value of a customer's last purchase. The graph below shows that it follows the actual value nearly perfectly. Additionally, this model saved significant development time by following the agile methodology.



Predictive solutions that consider data, such as the model showcased, enable marketers to take proactive steps towards maximizing campaign ROI and increasing overall revenue. Marketers simply do not have the capacity or ability to segment and analyze at the level artificial intelligence marketing solutions are able.

These solutions can help marketers succeed in cross-channel personalization and automation by predicting when to use specific content based on trends and benchmarks from large data sets.



THE SCIENCE BEHIND THE SOLUTION

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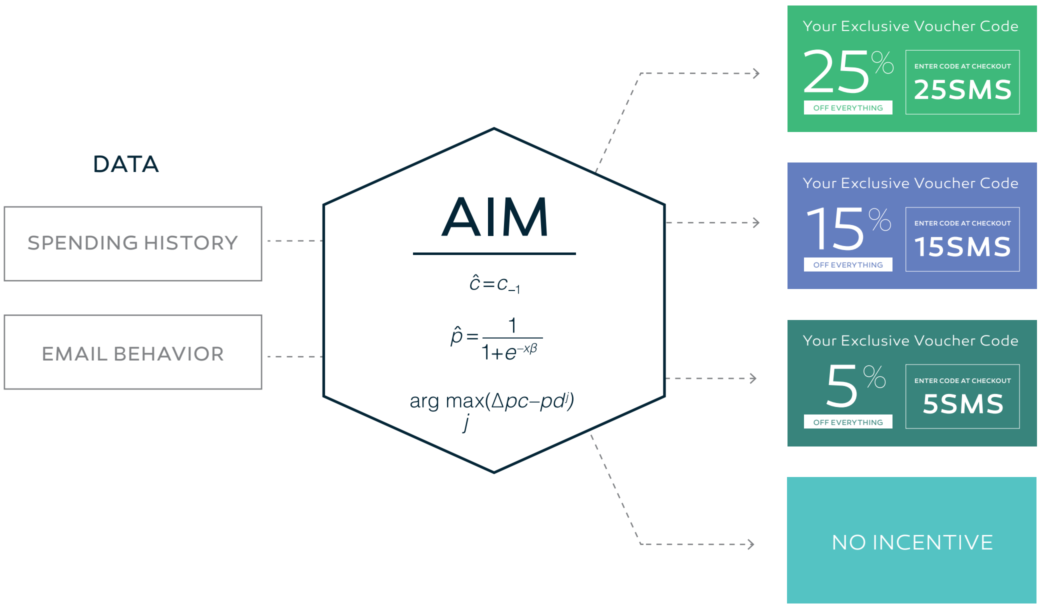
The solution can be described in the diagram below, where:

- **c hat:** Predicted cart value that is the amount of last purchase.
- **p hat:** Predicted value of buying probability that is the result of a logistic regression.
- **Arg max:** Given predicted values of p and c, and the effect of incentive on p (Δp), and the cost of incentive of type j (For example, 10% discount) dj, one can choose the type that brings in the most revenue in expected value.



To validate constantly improve assumptions, three random groups were set: one receives a personalized recommendation (smart), one receives the default 20% incentive (static), and one receives no incentive (control). The randomization ensured there were contacts with the same buying probability and cart value in each of the groups. Thus, the effects were measurable to constantly improve the model based on learning.

PRESERVING MARKETING RESOURCES, MAXIMIZING REVENUE

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When the power of AI is harnessed for marketing, it not only improves customer experiences and increases revenue, it also has the ability to decrease the marketing resources required for execution.

Advanced marketing technology platforms that incorporate AI allow the marketer to set up a campaign configuration once by defining possible incentives and establishing the overall strategy. From there, the cumbersome and endless fine-tuning to achieve 1:1 personalization is left to the 'brain' and 'hands' of artificial intelligence.

SOLUTIONS AND BENEFITS: WHAT'S POSSIBLE WITH AI

With the power of AI, it is possible to deliver truly personalized customer experiences that drive conversions and increase revenue.

PREDICTING PURCHASE PROBABILITY

Machine learning looks at all the data available for the contact, including purchase history and recency, to determine the probability they will make a purchase. It examines the predicted future value of that customer to determine what investment should be made to engage them. The findings are then combined to determine if and when they should receive an incentive, and if so, how large the incentive should be.

CALCULATING ANTICIPATED PURCHASE VALUE

The product of the probability of buying and cart value results in an anticipated purchase amount of each customer. This value can also be calculated for a range of different incentives by increasing the probability of buying appropriately and using the effect of the respective incentive.

DELIVERING PERSONALIZED INCENTIVES

By subtracting the cost of a given incentive from the anticipated purchase value it is predicted to generate, the optimal incentive for each individual customer can be identified. However, the process of selecting the optimal incentive remains a strategic question. It may seem like an obvious choice to select the incentive predicted to provide the greatest increase in profit. But, for example, a lead conversion campaign with a positive effect on probability of buying might be more important to the business.

CONCLUSION

The AI revolution is empowering marketers to deliver personalized incentive recommendations that will drive sales. AI and machine learning working together for marketing makes it possible for marketers to match incentives with customers on an individual level in a way that they simply could not manually deliver at scale.

Those who have already piloted such AI solutions for marketing this have experienced major uplift in their revenue. Read one brand's story in this case study: https://www.emarsys.com/en/resources/success-stories/evolution-slimming-aim/

ABOUT EMARSYS

Emarsys AIM solutions are easy for marketers to integrate and begin using immediately within the Emarsys platform – all with just the touch of a button. Leveraging the power of technology has never been easier. Learn more about AIM and schedule a personalized demonstration of Emarsys AIM solutions by visiting: https://www.emarsys.com/en/products/emarsys-aim/

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Phone: +1 844-693-6277 | Email: us@emarsys.com

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Emarsys USA | 10 W. Market Street Suite | 1350 Indianapolis | IN 46204 | USA
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