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Next Best Product Models for cross-selling financial services

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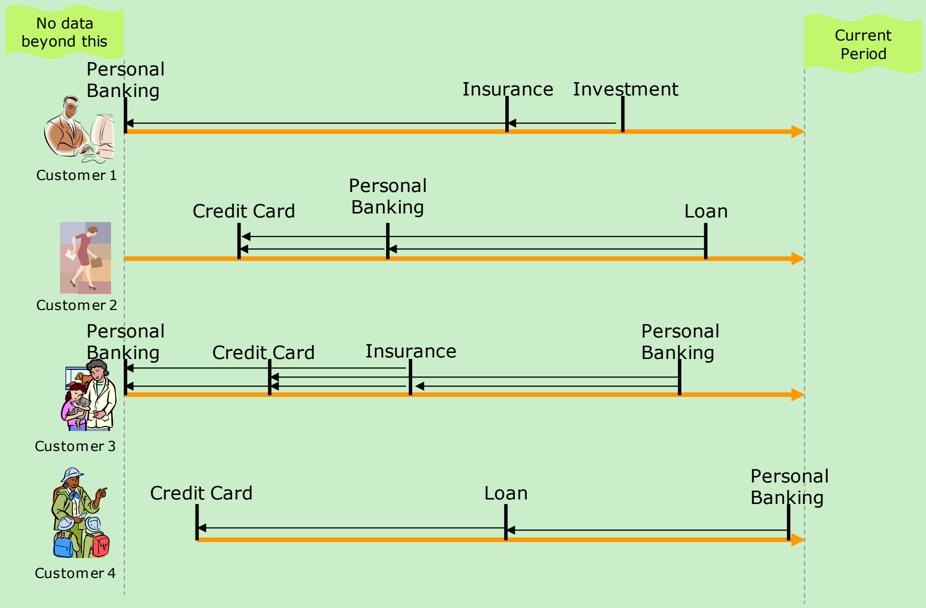
‘Next Best Product’ Models for cross-selling financial services

Abstract

‘Next Best Product (NBP)’ models refer to models that predict the next product/service/offer that a customer is likely to buy/use, given the customer’s previous purchase history in the same category. In this article, we present an NBP framework for financial services companies.

NBP models are particularly effective in cross-selling where data on past selling activity is not available (e.g., Relationship banking) or when there have been few co-ordinated cross-selling efforts. NBP models can also be used along with previous campaign response data to improve response rates.

We recommend an appropriate NBP technique for financial service firms, examine key analytical issues, and highlight a process for development and deployment.



NBP Technique

There are many techniques to analyze and predict the 'next best product' for customers. Regression-based approaches, neural nets, discriminant analysis, decision trees and collaborative filtering are a few common approaches. While most techniques work well, we have seen that ease of use and understanding, coupled with high predictive accuracy is what clients need. Table 1 illustrates the pros and cons of using different techniques.

Technique	Pros	Cons
Binary Regression based approaches	• Easy to use and implement • Most commonly used approach	Treats each product purchase as independent of the other since each equation models purchase of one product
Neural Nets	Handle interaction effects with ease (important for multiple product ownership)	Not as easy to understand
Discriminant Analysis	Easy to use and implement	Does not perform as well under violation of multivariate normality assumptions
Decision Trees	Easy to use and implement	Tree pruning requires skill and expertise
Sequence Analysis	• Results are intuitive and easy to understand • Works well when customers' buy many products (e.g., retail store) • Multiple levels of product hierarchy can easily be analyzed • Feasibility of automation	• Not suitable if most customers start with one or two products and their choices for next product is largely driven by usage of the existing product/s • Difficult to segregate natural attachment and attachment due to marketing stimuli

Table 1: Pros and Cons of various NBP techniques

We recommend using a **binary logistic or probit model with Markov Chain Monte Carlo (MCMC) estimation approach** to build NBP models for financial services firms. Logistic and probit models have a long established history in database marketing and targeting and are easy to understand, communicate and implement. While maximum likelihood estimation of these models is the norm, adding prior distribution knowledge through MCMC boosts efficiency and prediction accuracy (Refer to articles 9 and 10 under references).

NBP Modeling Process

Understand the data

1. Collect the data*
2. Analyze product purchase distribution, time between purchases and product ownership
3. Decide products for which models need to be built, and target customer population
4. Decide variables to be analyzed
5. Decide observation and history windows and time cutoffs

Clean and prepare the data

1. Sample data from population-create modeling, and validation samples
2. Treat missing observations
3. Treat multivariate outliers
4. Address skewness and kurtosis
5. Create new variables

Develop the Model

1. Develop binary logit/probit model with MCMC estimation for each product
2. Check for coefficient signs
3. Test for coefficient bias
4. Analyze product affinities and generate insights from models
5. Validate model using holdout sample and across time periods

Score and Target customers

1. Score all customers on each NBP model
2. Integrate NBP scores into IT system
3. Use NBP scores to identify campaigns to pitch to each customer (in conjunction with existing response models)
4. Score current customers every month

Monitoring and Implementation

Regularly track performance of NBP models by checking correlation of model predictions with actual purchase behavior

*The data required for NBP analysis include:

- **Demographic and socioeconomic profile** — age, marital status, number of children, occupation, education, etc.

- **Product Ownership and usage** — Opening date and closing date for each product/service account, monthly usage (value, number of transactions) for credit and debit transactions in each product/service account, monthly balance for asset/liability accounts
- **Campaign data (optional)** — marketing stimuli sent and response
- **Service centre data (optional)** — enquiries, complaints, etc.
- **Customer satisfaction data(optional)**

Key Analytical Issues

The following key issues need to be resolved for effective NBP analysis:

1. Identifying products to be modeled

If there is a typical sequential order for product purchase, it can be discerned by analyzing the sequence and timeline of customers that own a significant number of products. Analyzing the ownership percentage at various levels of the product hierarchy allows us to decide which products to model (e.g., Credit card vs. Balance Transfer/ Rewards/ Low APR cards; Savings account vs. Classic/Silver/Platinum Savings account).

2. Time periods chosen for analysis

The time period decisions are based primarily on the range of products for which models are being built and their history of purchase for a majority of customers. It may also be dictated by historical data availability.

3. Variable selection and creation

There is a need to pay special attention to variables like current product ownership, usage patterns, time since opening/owning each of the current products, Income/ wealth indicators, Gender, Education, and offers sent to customers and their responses.

Current ownership of products is usually a good predictor variable for the next product purchase. Information on response to previous offers in addition to purchase behavior helps companies target more effectively. If there is knowledge about the customer's competitors' product ownership, it should be incorporated into the model as well. We also advocate analyzing customer behavior in terms of usage patterns with the product owned. This maximizes available data utilization and simulates real life scenarios in terms of interactions among these important variables.

4. Model Evaluation

Ideally, the models must be evaluated on data taken from a time that does not overlap with that of the modeling population. We suggest that validation be done for the models on two sets of samples -one that is taken from the modeling population as holdout, and the other that is taken from a time period outside of the modeling population time period. This ensures that validation is robust and the models are stable and viable.

5. Piloting models before implementation

Once the NBP models are built and validated, we suggest piloting them in specific segments or regions. The pilots help iron out any issues that can arise at roll-out levels.

6. Model integration with business decision making

For the NBP models to assist business decisions, the scores must be coded into the IT system. A list of top potential customers for each product should be communicated to sales executives, customer service teams or advisors and call centre teams.

7. Assessing impact of models

The effectiveness of the NBP models must be tested continuously by using ‘control versus test’ experiments, where groups are set up to test whether the NBP models fare better in terms of generating product purchase as compared to the current business approach.

Organizations that aim to get better at cross-sell activities can incorporate Next Best Product models into their current efforts at no additional software related costs. The models can be built and scored outside the system and files with customer contact information supplied to necessary teams.

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