



# A Case Study on Building a Cross-Selling Model through Machine Learning in the Insurance Industry

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## Abstract

Cross-selling, has become widespread in recent years and has increased in importance, is a strategy of selling interrelated products or services to the customer by analyzing the general buying trend. In this study, firstly, its usage in data-based marketing and insurance is explained. As known, possibilities are very important in the insurance industry. For example, premiums to be determined in the next year in life insurance are based on the number of deaths (mortality) in the past years among certain age groups. Accordingly, the probability of customers with private pension contracts to obtain life insurance will be estimated. While making this estimation, besides the personal information of the customers, their behavior in the past periods of 1-3-6 months and the various traces they left on the system will be used. Machine learning, decision trees, and Cross Sales have been studied in detail. Customer data of an insurance company in Turkey is used in the implementation of the project. Then, it was examined whether a product can be purchased based on the past behavior of individual customers with the Chaid, C5.0 and Crt algorithms used in decision trees. Finally, it will analyzed that this study does not contribute to company sales, and new generation sales techniques will be used instead of traditional sales methods.

**Keywords:** Machine learning, Cross-selling model, Insurance, Decision trees.

## Sigorta Sektöründe Makine Öğrenmesi ile Çapraz Satış Modeli Oluşturma Üzerine Bir Örnek Çalışma

### Öz

Son yıllarda oldukça yaygınlaşan ve önemi artan çapraz satışlar, genel satın alma eğilimini analiz ederek müşteriye birbiriyle ilişkili ürün veya hizmetleri satma stratejisidir. Bu çalışmada öncelikle veri tabanlı pazarlama ve sigortacılıkta kullanımı açıklanmıştır. Makine öğrenmesi, karar ağaçları ve Çapraz Satışlar ayrıntılı olarak incelenmiştir. Projenin uygulama kısmında Türkiye'deki bir sigorta şirketinin müşteri verileri kullanılmıştır. Bilindiği üzere sigorta sektöründe ihtimaller çok önemlidir. Örneğin hayat sigortasında önümüzdeki yıl belirlenecek primler belirli yaş grupları arasında geçmiş yıllardaki ölüm sayılarını (mortalite) baz almaktadır. Bu doğrultuda bireysel emeklilik sözleşmesine sahip olan müşterileri hayat sigortası alma ihtimalleri tahmin edilecektir. Bu tahmin yapılırken müşterilerin özlük bilgilerinin yanı sıra 1 - 3 - 6 aylık geçmiş periyotlardaki davranışları ve sisteme bıraktıkları çeşitli izlerden faydalanılacaktır. Daha sonra karar ağaçlarında kullanılan Chaid, C5.0 ve Crt algoritmaları ile bireysel müşterilerin geçmiş davranışları üzerinden bir ürünün alınıp alınmayacağı incelenecektir. Son olarak bu çalışmanın şirket satışlarına katkısının bulunuo bulunmadığı analiz edilecek, geleneksel satış yöntemleri yerine yeni jenerasyon satış teknikleri kullanılmaya başlanılacaktır.

**Anahtar Kelimeler:** Makine öğrenmesi, Çapraz satış modeli, Sigortacılık, Karar ağaçları.

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## 1. Introduction

According to literature, the very first practices which are similar to insurance in the world date back to approximately 4000 years ago in Babylonia. In Babylon, which had become the trade center of its time, financiers that gave loans to caravan traders would write the debt off in the event that a caravan was robbed or a ransom situation arose and, in return for the risk they took, they would charge an extra amount in addition to the outstanding debt to be paid. This practice was later legalized by King Hammurabi. The most prominent aspect of the Code of Hammurabi was that it stipulated for the damages to caravans that were attacked by robbers to be shared among all other caravans. All assets, enterprises and securities belonging to people all over the world are under the threat of uncertainties referred to as "risks". Insurance involves compensation of the damages that arise for the insured in the event that the uncertain risks materialize.

This ensures for the uncertainty in the future to be eliminated for the insured. Insurance provides individuals and organizations with confidence in planning for the future. Insurance can also be defined as a sort of cooperation among people who are subject to essentially similar risks through unification of financial capabilities. The principal function of insurance companies is to bring people who are exposed to the same type of risk together and organize compensation of the damages that occur through use of a shared pool. When people who are subject to the same risk come together and face the materialized risk in unison, the amount to be paid by each person is decreased and even a major risk becomes affordable. The predictability of the amount of damages per person increases in direct proportion to the number of people who unite against the risk.

Insurance is a contract which is concluded between the insurer and the insured. The purpose of this contract is to establish an agreement in which the insurer indemnifies a pecuniary interest of the insured which can be protected legally against a potential situation of risk in return for a premium. The insurance policy, in which the details of the agreement are stipulated, contains the specific and general conditions that are individually stated.

In order for the insurance contract to have legal validity, it is essential for the parties to reach an agreement on key elements such as the risk against which indemnity will be provided, the sum to be insured, the subject matter of the insurance, the conditions of insurance and the premium. Insurance is not a source of revenue under any circumstances. The function of restoring the welfare of the insured to a state before the damages occurred renders insurance very important for both individuals and contribution to national economy.

As in all sectors, the customer is very important for the insurance sector. Since there are no goods or services produced and offered in the insurance sector, it is necessary to be there when the customer needs it. Because insurance is needed when the customer loses or damages anything that has a value on it. Like all commercial organizations, insurance companies need new customers to increase their profitability. Finding new customers and maintaining the satisfaction of existing customers is important in terms of customer relationship management. While determining customer relations, parameters such as the importance of the customer, the benefit it provides to the

company, and the number of services or products offered are taken into consideration.

The number of touch points between a customer and a company increases in direct proportion to the amount of additional products or services the customer purchases from the company. This, in turn, increases the switching cost for the customer. In addition, the more contact there is between the company and the customer, the more information the company obtains on the purchasing behaviors and preferences of the customer. This ensures for the company to acquire the skill of meeting the needs of the customer in a more effective way than its competitors. As a result, the company becomes able to increase both customer loyalty and customer profitability.

Our study includes a literature review which is as comprehensive as possible and is followed by an exploration of the fields of machine learning and cross-selling. The next phase involves a review of model building, followed by a comparative analysis of models.

## 2. Literature Review

This study involves two research areas in literature: cross-selling and supervised classification. A brief discussion on these two areas will be followed by a summary of the contributions of this study in relation to the aforementioned areas.

Unlike other CRM and direct marketing elements such as customer segmentation, customer targeting and customer management, there are relatively few studies in the field of cross-selling (Kumar et al., 2008). As discussed by Kamakura (2008), the analytical methods for cross-selling can be grouped in acquisition pattern analysis and collaborative filtering (CF). For the acquisition model analysis, the data from the previous purchases of current and other involved customers is used to define the next product that will be recommended (Kamakura, 2008). Kamakura et al. (2004) has developed a multi-dimensional acquisition model analysis and a multivariate split hazard model in order to predict the probability and timing of new product purchases. Prinzie & Van den Poel (2011) have considered customer purchasing behaviors as one-dimensional or multivariate sequences and implemented the mixture transition distribution model, Markov chain and Bayesian network in order to respectively model and predict behavioral data. Ansell et al. (2007) has combined customer lifestyle segmentation and proportional hazards model in order to determine cross-selling opportunities through use of demographic charts and the first five purchases of a customer. Kumar et al. (2008) has analyzed collective behavior characteristics, marketing efforts and product features on the statistical model for purposes of cross-selling and customer-targeting. [Ahn](#) et al. (2011) have used demographic and collective behavioral data as input to multiple classification models for cross-selling in the mobile telecommunications industry and utilized genetic algorithms to find solutions. In the last decade, CF has caught the attention of researchers in the field of computer sciences and is widely used for recommendation systems in the area of electronic commerce. ICF, UCF and matrix coefficient (MC) are three CF methods which are commonly used Bellogin et al. (2013). MC has recently become one of the mainstream recommendation algorithms (Bellogin et al., 2013). Li et al. (2011) has applied a multivariate probit model in order to predict customer responses for cross-selling recommendations. Later on, they suggested a stochastic dynamic programming model to reach decisions regarding cross-selling

recommendations for the purpose of taking temporal customer demand and the long-term effects of cross-selling promotions into consideration. [Netessine et al. \(2006\)](#) has used product stock and customer preference probability distribution data as input for cross-selling and pricing of packaged products. The most significant contribution of this study is inclusion of polycentric multi-directional data in classification models for purposes of tensor-based classification and cross-selling recommendations for improving classification performance and customer response rate in particular. In the past, customer demographic and collective behavior data, which was represented by matrices, was generally used as input for standard cross-selling models ([Ansell et al., 2007](#); [Ahn et al., 2011](#); [Chen et al., 2013](#)). For IF, purchasing samples related to customers and products are used in order to identify cross-selling opportunities and recommend additional products to customers ([Bellogin et al., 2013](#); [Kamakura, 2008](#)).

### **3. Machine Learning and Cross-Selling**

Machine learning is often confused with the field of data mining. The primary reason behind this is the fact that the methods used are very similar for both. Data mining can be defined as processing of collected and recorded data with mathematical and statistical methods for the purpose of generating significant results. This endeavor also constitutes the first step of machine learning. However, the process of machine learning involves not only exploration of the collected data but also prediction of future events through use of this data.

When viewed as a process, data mining generally ends when the targeted information is acquired but machine learning continues the learning process with each bit of information that is acquired and constantly improves itself. While the name “machine learning algorithms” causes hesitation in people’s minds, these algorithms are essentially based on a very simple logic. If we were to summarize this logic in three steps, we could say that it requires us to follow the order of “watch, learn and apply”. To clarify the issue with an example from daily life, we can take a look at the students who prepare for university admission exams each year. Since these exams are in the form multiple-choice tests and require students to answer a specific number of questions within a limited period of time, factors such as the students’ level of familiarity with the questions, speed in answering the questions and grasp of the subject affect the results directly. At this point, the students make an effort to both learn the subjects within scope of the university exam and increase their knowledge on these, and form an understanding of the exam itself by examining the questions asked in the previous years. Analyzing and answering the questions from previous years provides the students with an idea on the structure and form of the questions as well as the paths to take while coming up with the answer, and at the same time increases their speed in answering by familiarizing them with the question types.

The more questions a student answers, the higher their level of familiarity becomes, and the faster and more accurately they answer the questions. This is the same logic as the one adopted in machine learning: “Watch, learn and apply.” Regardless of the purpose, a prediction model must have high accuracy. Precision and specificity are assessed on the basis of the types of error we deem to be critical and costly. In some cases, a researcher can focus on precision or specificity alone. In other cases, having balance for both can be important for the researcher. Through the cross-selling model included in our study, we will predict the

purchase probability of customers who have not purchased the R1 product. As a result of this prediction, sales actions are defined for customers with a high probability of purchase. Based on this example, an indication by our model for high purchase probability in relation to customers who are, in reality, not likely to make a purchase would lead to unnecessary sales attempts and create costs. In such a case, the error that must be avoided is prediction of high purchase probability for customers who are unlikely to make a purchase. A prediction of low purchase probability for a customer who is likely to make a purchase, on the other hand, does not create costs but has an effect on the accuracy of our model.

### **4. Cross-Selling**

It is a generally accepted fact that selling a product or service to a new customer is five times as costly as selling it to an existing customer. This makes cross-selling very appealing for many marketing specialists. Despite being a new concept in marketing, cross-selling is a term that is frequently encountered in daily life (in grocery stores, restaurants, banks, etc.). Cross-selling is an idea that has gained popularity towards the end of the 20th century. Basically, it involves selling more products of different types and brands to the same customer. In a broader sense, it consists of selling a customer who has already purchased a product or service from a company an additional, different product or service. According to the Economist, cross-selling is a synergic concept which defines the way in which a person that has purchased a service from a company once again attains customer status for another service from the same company. The objective is to make another sale in addition to the product or service a customer is convinced to purchase or has already purchased. Selling to an existing customer increases both the revenue of the company and the revenue acquired from the customer in question. Furthermore, it costs less than acquiring a new customer. Notwithstanding this fact, factors such as selecting the customer, the effect of the customer profile on cross-selling and choosing the right time for cross-selling play a major role in achieving success.

### **5. Model Building**

In this study, IBM SPSS Modeler (SPSS Clementine) version 18.0 has been used in the stages of data preparation, data cleaning and running of machine learning algorithms. Modeling will be performed in accordance with the CRISP-DM methodology shown in detail in Figure 1.

During calculation of the current value segmentation to be used as input in the study, the first activities were data exploration, examination of the distributions and grouping as per the 80/20 rule. In general, a rule-based structure was preferred. The following section includes detailed information without revealing the structure of the model. Of the 86 variables listed 6th section, the ones that were likely to be used in the model were examined through logistic regression and those that caused multiple correlations were eliminated in the first stage.

There are a total of 686,811 active and passive policies belonging to 192,966 customers included in the sample. Among these customers, 45,214 have previously purchased the R1 product (including both active and passive) while 147,752 are customers that have previously purchased products that are different than R1. The values are shown in Table 1.

## 6. Dataset

While creating the dataset, it is basically divided into 4 main categories. These categories are; It consists of customer demographic information, financial information, customer contact points, product information and results generated from other analytical models linked to the relevant customer. Below are examples of data for each category used in the model.

### Demographic Dimension

- 1- Age of Customer
- 2- Gender
- 3- Education Status
- 4- Profession
- 5- Marital Status
- 6- City of Residence
- 7- District of Residence
- 8- Number of Children
- 9- Customer Segment
- 10- Job Title

### Product Ownership

- 11- Active Product Flag
- 12- Active B1 flag
- 13- Active H1 Flag
- 14- Active F1 flag
- 15- Active O1 flag
- 16- Active O1 External B1 flag
- 17- Active SH1 flag
- 18- Active KH1 flag
- 19- Active IG1 flag
- 20- Active GB1 flag
- 21- Number of Active Product
- 22- Active B1 unit
- 23- Active H1 unit
- 24- Active F1 number
- 25- Active O1 unit
- 26- Active O1 External B1 number
- 27- Active SH1 pieces
- 28- Active KH1 unit
- 29- Active IG1 number
- 30- Active GB1 pcs

### Product Ownership

- 31- Number of products purchased in the last 1 year
- 32- Number of B1 taken in the last 1 year

- 33- Number of H1s taken in the last 1 year
- 34- Number of F1s taken in the last 1 year
- 35- Number of O1 taken in the last 1 year
- 36- Number of B1 other than O1 taken in the last 1 year
- 37- Number of SH1s taken in the last 1 year
- 38- Number of KH1 taken in the last 1 year
- 39- Number of products purchased in the last 3 years
- 40- Number of B1s taken in the last 3 years
- 41- Number of H1s taken in the last 3 years
- 42- Number of F1s taken in the last 3 years
- 43- Number of O1 taken in the last 3 years
- 44- Number of B1 excluding O1 taken in the last 3 years
- 45- Number of SH1s taken in the last 3 years
- 46- Number of KH1 received in the last 3 years
- 47- Is BES its first product?
- 48- Is his first product Life?
- 49- Is his first product FKS?
- 50- Max active product life time
- 51- Year of first product purchase

### Channel Information and History

- 52- Active Bank flag
- 53- Active DSF flag
- 54- Active Agency flag
- 55- Active Corporate flag
- 56- Active Telesales flag
- 57- Multichannel flag
- 58- Number of Active Banks
- 59- Active DSF number
- 60- Number of Active Agents
- 61- Active Corporate Number
- 62- Number of Active Telesales
- 63- Last 3 years Bank flag
- 64- Last 3 years DSF flag
- 65- Last 3 years Agency flag
- 66- Last 3 years Corporate flag
- 67- Last 3 years Telesales flag

### Financial

- 68- Bulk payment in the last 1 year flag
- 69- Total B1 savings amount
- 70- Total B1 monthly payment amount
- 71- Total non-B1 premium



- 72- Critical illness coverage flag
- 73- Unemployment benefit flag
- 74- Has he taken a break in the last 3 years?
- 75- Have there been any cancellations in the last 3 years?
- 76- Active CC Payment Flag
- 77- Active Remittance Payment Flag
- 78- Payment from Active Account Flag
- 79- Active Other Payment Type Flag
- 80- Payment in the first 10 days of the month
- 81- Payment on the second 10 days of the month
- 82- Payment in the last 10 days of the month
- 83- Annual payment period flag
- 84- 6 month payment period flag
- 85- 3-month payment period flag
- 86- Monthly payment period flag

Table 1. Sample distribution and state of balance

	Sample	
Total	192,966	100%
R1 Buyer	45,214	25%
Non-R1 Buyer	147,752	75%
Training	112,748	65%
Test	75,240	35%

The preliminary preparation process was followed by the model building stage. The first step in this stage involved analysis of the data quality for the 86 variables that would serve as input for the model, elimination of deviating values and data transformation to render blank and invalid records meaningful. The process was continued until the fullness and quality ratio of each colon was 100%, and the deviating values were minimized.

Following the completion of the required cleaning procedures for the data, the distribution of the R1 product purchase state, which was the target variable, was checked in order to avoid biased results from the model. The requirement for the number of buyers and the number of non-buyers in the distribution to be close is an important prerequisite for model building. The sample of 112,748 people in total consisted of 20,754 (23%) R1 buyers and 91,994 (77%) non-R1 buyers. The lack of balance between these ratios indicated the necessity of balancing for model building.

In accordance with the result variable, the number of non-R1 buyers were balanced with a ratio of 0,25 and reduced to 22,822. As per the new results following the balancing, which are shown in Table 2, the number of R1 buyers was 20,754 (47%) while the number of non-R1 buyers was 22,822 (53%) in the distribution.

Table 2. Record numbers before balancing

Buying-Non_Buying	Partition	Record_Count
1	1_Training	20754
0	1_Training	91994
0	2_Testing	61142
1	2_Testing	14098

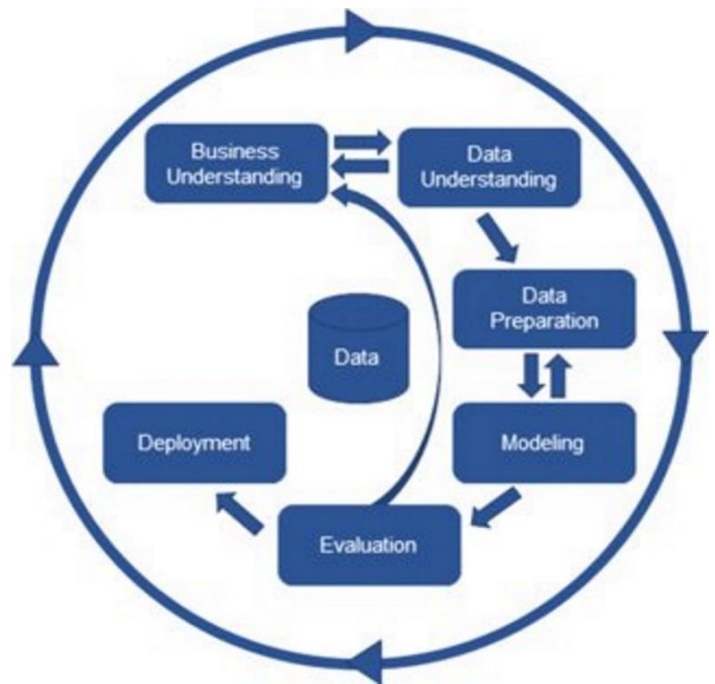


Figure 1. CRISP-DM Methodology cycle

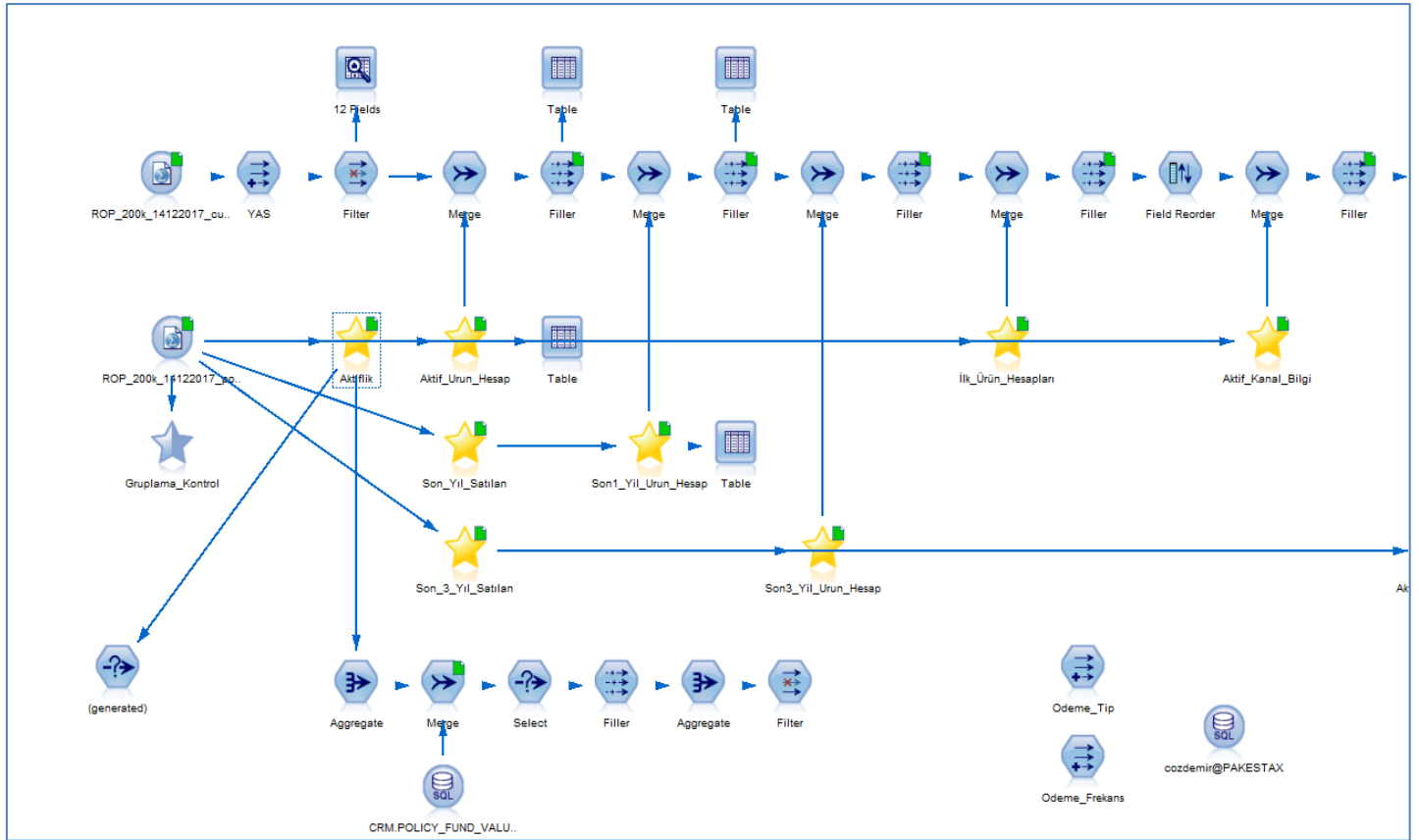


Figure 2. Collection of data and the established model flows (summary)

The model shown in Figures 2 and 3 was built and the accuracy calculation of the model was performed through use of 3 decision tree algorithms. The decision tree algorithms that were used while the models were being built and the success ratios of the models are specified in detail in Table 3.

## 7. Comparison of Model Results

An examination of the results of the 3 decision tree models in which the customer variables was given as input reveals the strongest model as the one produced with the C5.0 algorithm through the training data. The performance of all 3 models in prediction of the output state was very close and varied between 98 to 99%.

At this point, since we could not use champion model structure, it was essential to lean on 2 criteria while deciding which model to choose. Choosing an algorithm which had high training data performance and did not involve a large difference between training and test data performance (i.e., one that was consistent) was of great importance in avoiding large future deviations in the model. Since the results acquired with the selected 3 algorithms were very close, we performed an ensemble procedure in order to use them all and ensure for them to provide accuracy for each other. With this ensemble procedure, using averaging model another model result was produced through blending of the variables with the highest explanatory power from the 3 models

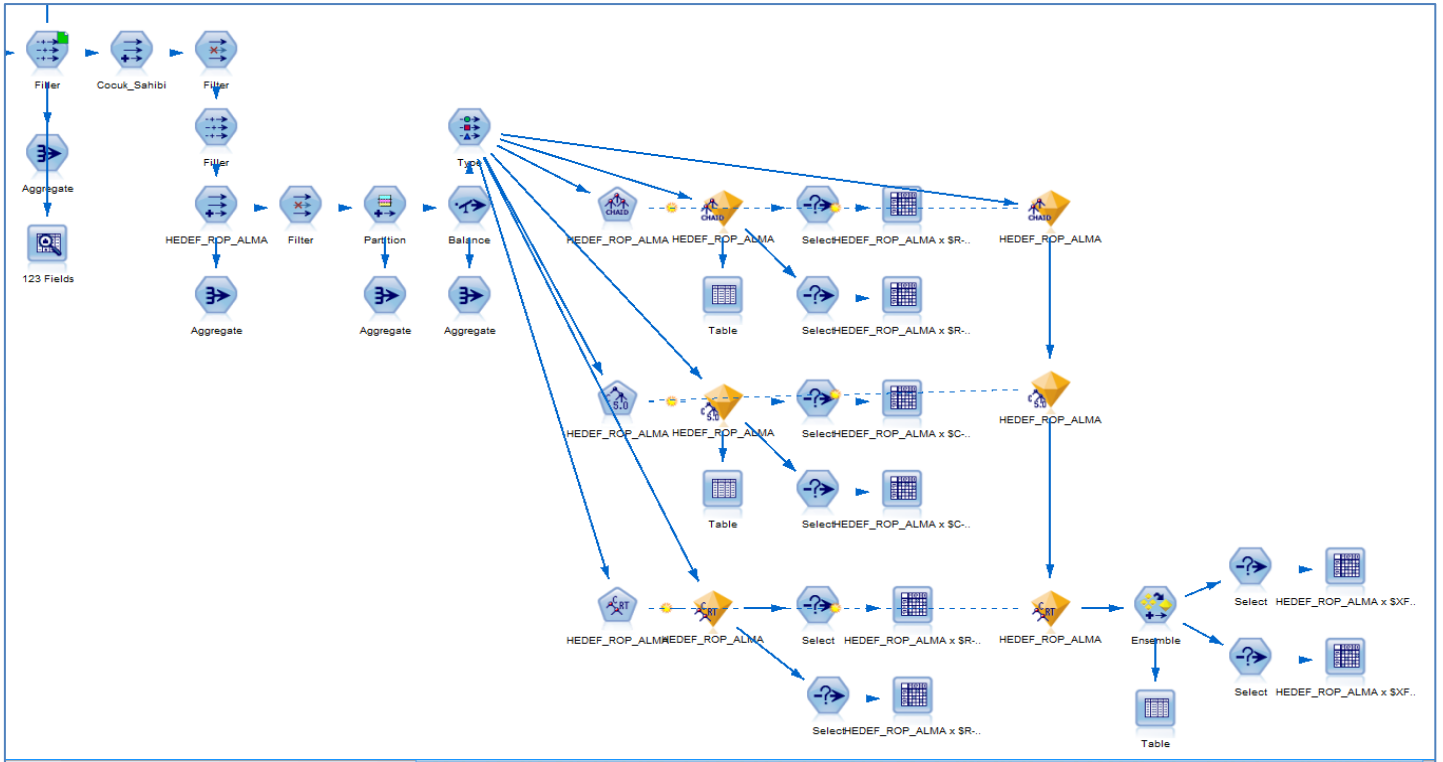


Figure 3. Collection of data and the established model flows (continued)

Table 3. Training and test results for the model results

Chaid Training		Predicted	
		Purchase	No Purchase
Actual	Purchase	22458	422
	No Purchase	235	20519
Total		43634	
C5.0 Training		Predicted	
		Purchase	No Purchase
Actual	Purchase	23031	128
	No Purchase	41	20713
Total		43913	
C&Rt Training		Predicted	
		Purchase	No Purchase
Actual	Purchase	22459	588
	No Purchase	374	20380
Total		43801	
Chaid Test		Predicted	
		Purchase	No Purchase
Actual	Purchase	60084	1058
	No Purchase	172	13926
Total		75240	
C5.0 Test		Predicted	
		Purchase	No Purchase
Actual	Purchase	60764	378
	No Purchase	33	14065
Total		75240	
C&Rt Test		Predicted	
		Purchase	No Purchase
Actual	Purchase	59718	1424
	No Purchase	302	13796
Total		75240	

Table 4. The result acquired after the ensemble procedure

Target_Rop_Purchase		0	1	Total
0	Count	22872	102	22974
	Row %	99,556	0,444	100
1	Count	87	20667	20754
	Row %	0,419	99,581	100
Total	Count	22959	20769	43728
	Row %	52,504	47,496	100

As shown in Table 4, the prediction ratio of the result acquired after the ensemble procedure is over 99.5%.

## 8. Conclusion

We are aware of the potential of our customers to sell one more product in our world, where 80% of them are a single product. At the same time, this is actually very difficult in life, and at this point, we embarked on this cross-sell modeling journey to harness the power of data.

We know that propensity scores alone don't mean much. The point where data analytics modeling results take action must be a strategy, a customer experience journey and a common point with the goals of the salesperson. As a result of the cross selling trend we made, a purchasing trend score was obtained for each customer and each product. Different strategies were prepared for each category along with the propensity scores as well as other features. Here, the point we make the most use is the customer's value segment and behavior segment, the customer's return rates, and micro segments were created according to the usage of the app, and special scripts and communication models were prepared for these micro segments.

In these breakdowns where customer behaviors and sensitivities are different, customers with high customer returns are approached with affirmation and a new product that they can actually think about is presented. On the other hand, a product recommendation was offered to our customers with families with a special script.

Communication channels have been differentiated for some of our customers. First of all, in order to raise awareness, sms and mails were sent, and then tasks were assigned to the field communication channels through the company CRM to touch a certain audience one-on-one. We measure the field success of this paper by collecting the soft responses of these tasks and at the same time bringing the hard responses to them. At the same time, unlike testing, in the modeling process, we also separate a population that has a product-buying tendency score but cannot be assigned to the field as a test. In this way, it is possible to compare the sales realized spontaneously without communicating with the customers who reach the result with communication.

We compared the cross-product sales studies with customers we had done in the previous periods and the actual results based on the results of the cross-selling modeling. Here, we found a 25% positive increase. We see the 25% increase as a very valuable increase in a standard work where we move forward with a smarter, targeted list and communication channel towards the right segment. Nowadays, it is difficult to sell a product to the

customer, and with this work, our customers, who have only one product, have been reduced from 80% to 75%.

When the customer buys a second product, it also helps to establish stronger relationships by increasing the loyalty of the customer within the scope of loyalty. These customers gradually move to the top segment customer profile. In addition, segment ranges and customer profiles are updated every year and missing parts are revised

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