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Use of predictive analytics in B2B sales lead generation

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Abstract

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The aim of this study is to investigate the possibilities of using predictive analytics as a part of the B2B lead generation in the case company Fonecta. The target is to examine how predictive analytics is used in the current lead process as well as identify areas of improvement and new possibilities of using predictive analytics.

The theoretical framework of this study describes the two main domains related to this study: B2B lead generation and predictive analytics. The theoretical framework covers in more detail the different areas of predictive analytics, including the related machine learning algorithms as well as specific applications of predictive analytics in marketing.

The current lead generation process and the use of predictive analytics in the process was examined based on documentation review and workshops with the stakeholders.

Pilot cases for testing new ways of using predictive analytics in the lead process were selected based on discussions in the workshops that were held for the stakeholders. The pilot cases were run for a two month period after which the results were analyzed and validation of the selected predictive model was carried out. No statistically significant results on the pilot cases were achieved during the pilot period.

Main suggestions for future includes extending the selected pilots cases for a longer period in order to gain significant results as well as the utilization of behavioural data as a part of the predictive model.

Keywords
predictive analytics, lead generation, B2B marketing, marketing automation, machine learning

Table of contents

1 Introduction

Fonecta is a marketing partner for Finnish companies in digital marketing and data services. The product offering covers a variety of different solutions for companies, including solutions for web presence, digital advertisement as well as data and analytics services. Fonecta offers solutions to companies of all sizes but majority of the current customer base consists of small and medium sized companies (SMEs). Currently it has approximately 40 000 business customers.

Lead generation has been a fundamental part of Fonecta's B2B marketing for the past three years. In 2015 the company started to use and develop lead generation and marketing automation in a systematic way which have yielded promising results, especially with the SME companies. Currently around 30-40 % of sales to SMEs are done based on leads.

Focus has been on constant and iterative development of the lead process, until now it has concentrated more on implementing cultural change which has been one of the key aspects of successful adoption. As the process starts to be more mature the efficient use of predictive analytics is increasing its importance for future success.

Predictive analytics offers possibilities in several ways when integrated into the lead generation process. It can help to identify and prioritize sales leads allowing personnel to focus on the most profitable customers – as unqualified leads cost valuable time and money. Predictive analytics can also support implementing personalized messaging with customers in order to deliver excellent customer experience which is more important than ever in today's digital world. (Hale 8 May 2018.)

Use of accurate business intelligence will be a differentiator for companies in the future. Hale (8 May 2018) outlines a simple reason why every company should be using predictive analytics: "Go beyond learning what happened and why to discovering insights about the future, and you'll better serve your customers today."

2 Objectives and research questions

The purpose of this study is to investigate the current use and future possibilities of using predictive analytics as part of the lead generation process.

The three main objectives of the study are to:

- Identify new ways of using predictive analytics in the lead process.
- Select use cases and pilot using predictive analytics in new parts of the lead process.
- Analyze if using predictive analytics had any significant improvements in the selected pilot use cases and make recommendations for future.

Based on the objectives the main research questions for this study are following:

- **RQ1:** How are predictive analytic methods used in different parts of the company's lead process at the moment?
- **RQ2:** How could use of predictive analytics in lead generation be improved?
- **RQ3:** How can the results of the pilot use case be analyzed and reported?
- **RQ4:** What are most promising use cases for future development?

The scope of the development project is to assess the suitability of using predictive analytics in the selected areas of Fonecta's own lead generation process. More use cases and development areas might be found during the study but those are out of the scope for this thesis. Recommendations for future are constructed during the thesis but taking them into production use is not in the scope.

3 Methodology

This study was carried out between March 2018 and November 2018. The related pilot cases were run between September 2018 and October 2018. Study was conducted as a case study and as an action research. The results from this study are specific for the target organization's processed and cannot be generalized. The study aims to iteratively improve the use of predictive analytics in lead generation. People involved in the study are working closely with the lead generation activities which is why action research was selected.

3.1 Data collection

Data was collected through workshops, literacy and documentation review and by gathering data from CRM (Customer Relationship Management) and marketing automation systems.

Literacy review was conducted in the beginning of the study to find a suitable model or models for using predictive analytics in the pilot cases of this study. The review covered different areas of predictive analytics and machine learning as well as their possible applications in marketing.

Two workshops were held regarding the development project: first one in June 2018 and second one in October 2018. Key persons involved in the lead generation process participated in both workshops: stakeholders from analytics, lead generation and marketing functions. In workshops existing solutions for predictive analytics were opened up in detail in order to gain mutual understanding of the current way of working. After that brainstorming was used in order to gain ideas for pilot cases or other future development ideas for using predictive analytics.

After the selection of the pilot cases data from the CRM system was extracted as the analytic dataset for the selected predictive model. Leventhal (2018, 27) describes five steps of data preparation for predictive models which were carried out also in data preparation part in this study:

1. Data selection: selection of the leads and attributes to be included in the dataset.
2. Data cleansing: removal of lead data that could not be mapped to a certain product or lead data that was not relevant for the model.
3. Constructing data: mapping of the lead data with existing attributes in the model.

4. Integrating data: merging of the lead dataset with the existing dataset containing data of sales calls performed by the sales personnel.
5. Formatting data: formatting of the lead data so that it could be imported in to the predictive modelling software.

As new relevant lead data was created in the CRM system also during the pilot period, the data was automatically integrated as a part of the training data for the predictive model. This allowed the model to learn and gather new training data also during the pilot period.

3.2 Data analysis

Results from the pilot cases were gathered from both marketing automation and CRM systems. The response rates for the selected pilot cases were gathered from the marketing automation system: number of email deliveries, opens and clicks. Lead hit rates were collected from the CRM system. Lead hit rates provided indication about the lead quality in the pilot cases.

The quantitative data about the pilot cases was gathered from the CRM and marketing automation systems on November 8th, a week after the pilot period was over. One week period before the result extraction was needed in order for most of the email opens and clicks to accumulate.

Number of opened emails is a fairly unreliable metric for engagement as it is dependent on the respondent downloading images in the email in order to trigger a tracking pixel. Therefore the number of opens is reported in the results but it was not used for assessment of the model. Number of clicks compared with the delivered emails was considered as the most important indicator for customer’s engagement with the email content. For that reason the click-rate in the emails was selected as the most important factor when analysing the validity of the predictive model.

History data about the same campaigns during September 2017 and October 2017 was extracted from the marketing automation and CRM systems for comparison and validation of the predictive model.

3.3 Validation

The validity of the predictive model was assessed by comparing the results for each of the pilot case campaigns with the results in the same campaign in 2017. Due to technical limitations simultaneous tests with the previous and new versions of the predictive models were not able to be carried out so the most relevant point of comparison was found to be the same campaigns in 2017.

The assessed metrics included number of delivered emails, number of opens, number of clicks and hit rate to leads. As stated earlier the click-rate in the emails was selected as the key factor for analysing the validity of the predictive model. The results of each email campaign were tested for statistical significance using 95 % confidence level and two-tailed test in order to see if the new predictive model has caused changes in email engagement to either direction. The statistical tests compared number of delivered emails and number of email clicks for each of the campaigns in 2017 and 2018.

The lead hit rate for each of the campaigns was analysed and compared to results in 2017. As the data was extracted only one week after the pilot period it is possible that the hit rate for the pilot campaigns will improve over time. Therefore the lead hit rate was only used as an indicative metric in addition to the email metrics.

4 Lead generation in B2B marketing

There is no universal definition for a lead – appropriate definition for a lead depends on the company's processes. Most often a lead is defined as someone who has been identified to have shown interest in the company's products or services. (Flaherty 7 June 2018.)

Lead generation is the process of converting interest to the company's products or services into actionable information: names and contact details that the sales team can pursue (Fleming 1 June 2017). This is often seen as the main goal and measurement for B2B marketing (Paul & Schwartzman 2010, 157).

Previously B2B marketers have been doing this for example by sales calls or attending trade shows. Traditional outbound marketing has utilized mass communications like advertisements, events and direct mailings as lead generation tools to attract prospects. (Paul & Schwartzman 2010, 157-158.)

In the digital world more methods are now available, for example through search engines and social networks. These new digital lead generation channels are able to bring the same results as traditional channels but often more cost effectively. (Paul & Schwartzman 2010, 157-158.)

4.1 B2B lead generation channels

According to Hillsberg (10 July 2018) the most important channels for B2B lead generation include social media, pay-per-click advertising, blogging and email.

Social media as a lead generation channel has fairly good reach but it has been estimated that social media has often lower conversion rates compared to other digital channels for B2B lead generation. Wide reach makes it a good channel for example for building awareness by promoting an e-book. The most relevant B2B social media at this time is LinkedIn. (Hillsberg 10 July 2018.)

Pay-per-click (PPC) lead generation campaigns can cover a number of different platforms, most often used are Google AdWords and Google Display Network. PPC advertisement is an efficient way to support the organic visibility when thinking of lead generation. (Hillsberg 10 July 2018.)

Blogging can be used as a channel for creating interesting and valuable content for selected audiences. It will help to attract people to the company website and convert that traffic to high quality leads. (Hillsberg 10 July 2018.)

Email marketing is an essential part of lead generation: in 2014 it was selected as the best digital marketing channel for B2B by Chief Marketer study. In 2016 in State of B2B Digital Marketing Report it was top of digital channels for generating leads in US B2B market. Predictive analytics and artificial intelligence algorithms that are available today enable the use of email as targeted and personalized marketing channel. (Hillsberg 10 July 2018.)

All of these channels can be used in combination with inbound marketing to drive traffic at the top of the inbound marketing funnel. Inbound marketing is covered more in-depth in the next chapter.

4.2 Inbound marketing model

Inbound marketing model is based on observing the customer’s actions and generate lead when those actions indicate that they are ready to buy (Paul & Schwartzman 2010, 158). The key aspect is that the potential customer is exposed to company’s relevant content when searching for information proactively. In order to get access to this relevant and valuable information (typically for example e-book or whitepaper) the prospect usually is obliged give their contact information in return. Important aspect is that the prospect is opting in to receive the information from the marketer. Inbound marketing model is based on the company demonstrating know-how on the topic and building trust with the potential customer. (Kurvinen & Seppä 2016, 189.)

When the potential customer has entered in the inbound marketing funnel the company tries to predict potential customer’s needs and communicate them with messages targeted for that specific stage in the buying process where the prospect is in. With the targeted messaging the potential customers are being nurtured towards making a purchasing decision. (Paul & Schwartzman 2010, 157-158.)

Often this can be more productive than traditional marketing channels, like advertising and direct mail, which focus on broad reach and frequency to reach the potential buyer at the right moment. Example of inbound marketing process is illustrated in the Figure 1. (Paul & Schwartzman 2010, 157-158.)

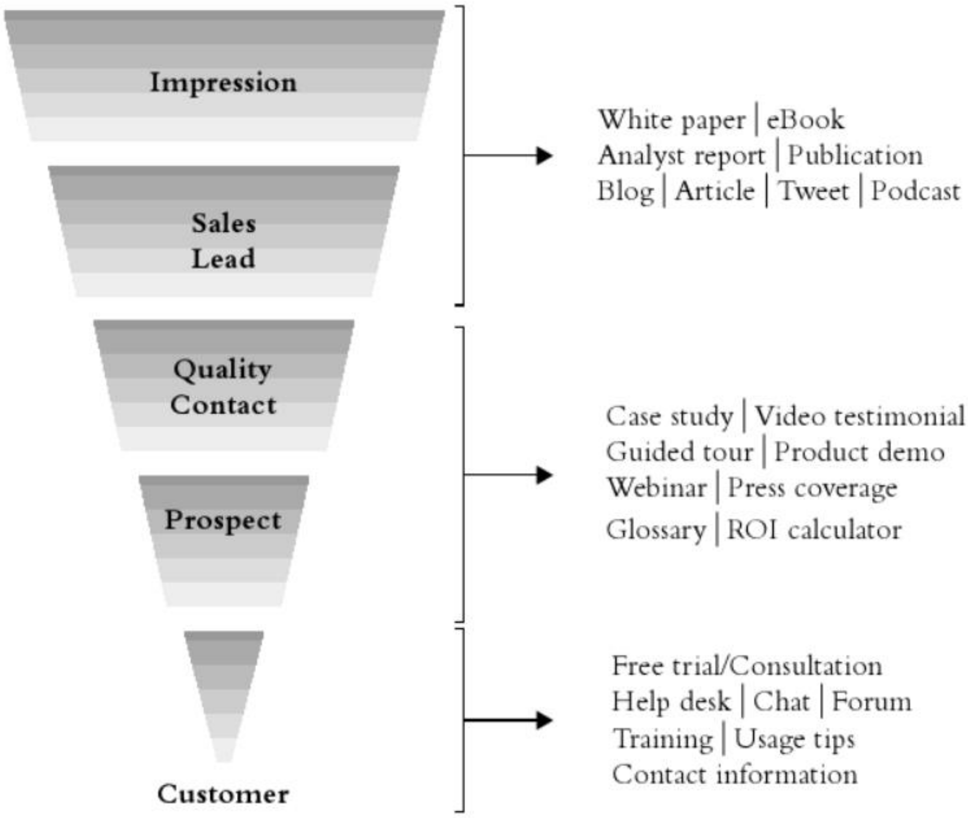


Figure 1. Example content along buyer's journey in inbound marketing lead generation process (Paul & Schwartzman 2010, 157-158)

The information about the customer will typically transfer automatically to the marketing automation system. Based on the downloaded content the lead can be categorized as a sales ready lead or someone just indicating their interest in the topic. Lead nurturing processes can be automated to further qualify or warm up the leads that are not yet considered to be ready for sales. (Kurvinen & Seppä 2016, 197; Halligan & Dharmesh 2014, 125-128.)

According to Kurvinen and Seppä (2016, 189) the marketing objectives in inbound marketing can be divided to four different stages: attract, convert, close and after care. Process and typically used tactics are illustrated in Figure 2.

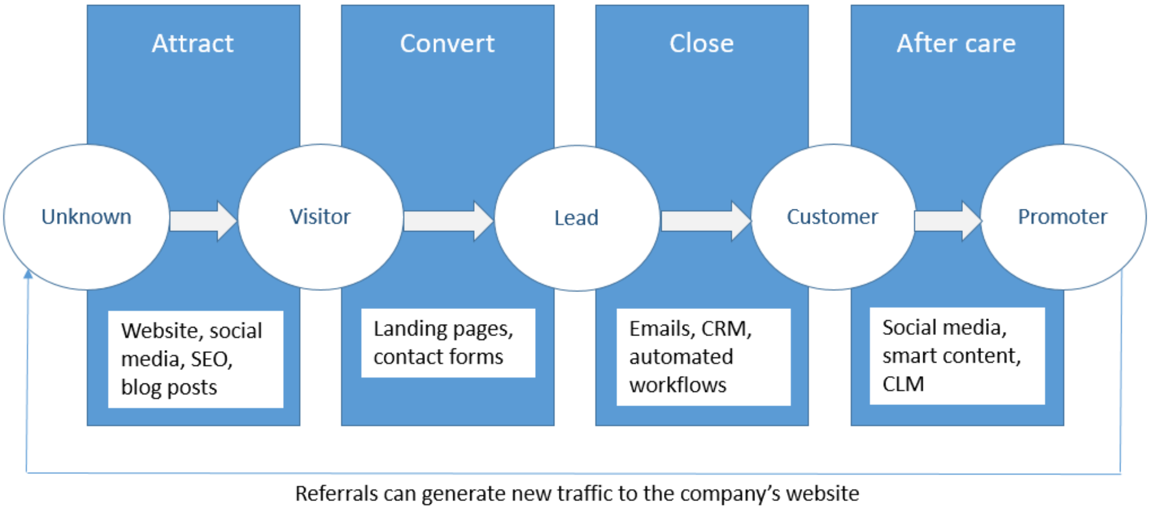


Figure 2. Inbound marketing process (Kurvinen & Seppä 2016, 189)

Interesting and high-quality content is one of the most effective ways to attract visitors to a company's website. Organic visitors generated through web searches are very interesting from company's point of view because they have an identified need. Other fairly used tactic is also utilizing social media channels and be involved in the discussions in the social media. (Kurvinen & Seppä 2016, 190-191.)

The goal is to convert the visitor into a lead by getting the customers contact information and marketing permission. Landing pages and contact forms for downloading content usually include asking for the consent. (Kurvinen & Seppä 2016, 192.)

Closing stage is focused on identifying the most potential leads for turning into a customer. This will help to allocate sales resources to right leads. (Kurvinen & Seppä 2016, 196.)

Last stage is after care. Often B2B companies are guilty for forgetting their customers after closing the sale: the next touchpoint is usually the invoice. Website personalization or onboarding messages are effective ways to improve customer experience for exiting customers. (Kurvinen & Seppä 2016, 200-201.)

4.3 Role of marketing automation

Lead generation and inbound marketing are often implemented with the help of marketing automation which analyses data gathered from different digital touchpoints. Marketing automation solutions can provide useful insights about the potential customers: for example about role in the company, consumed content, topics of interest or in which channels the person is most active in. (Rubanovitsch 2018, 84; Kurvinen & Seppä 2016, 197.)

With the collected data, marketing can more accurately target the persons who show the most potential for buying. Those can be for example people who have filled out a form in the web page or subscribed to blog posts. Often marketing automation solutions offer also a lead scoring solution which can help to identify the most potential leads. Data collected into the marketing automation system also helps to target future messages to relevant customers and through that also deliver value to the customer. (Rubanovitsch 2018, 84; Kurvinen & Seppä 2016, 197; Halligan & Dharmesh 2014, 125-128.)

Marketing automation and automated workflows allow companies to effectively take potential customers through the buying process. Often the process can be set up based on predefined rules and is used to automate the communication to the leads. (Kurvinen & Seppä 2016, 197.)

Sales ready leads can be transferred to the CRM system automatically with all the relevant data about different touchpoints with the lead. Information will assist sales to modify their sales approach based on the lead action. Keeping track of the lead source will enable to report return of investment on marketing activities. (Kurvinen & Seppä 2016, 197.)

4.4 Lead qualification

The quantity of leads is often seen as the most important measure in B2B marketing but it is important to measure also the quality of the leads. Quality in this context means the leads that are most likely to turn into good customers. Measuring quality in addition to quantity will help to assess the effectiveness of the marketing efforts and focus sales resources to the most potential leads. (Halligan & Dharmesh 2014, 125-128.)

Qualification process can use collected data, proprietary data as well as behavioral data to measure the lead quality (Kurvinen & Seppä 2016, 269). According to Halligan and Dharmesh (2014, 127-128), useful metrics to define lead quality include the following:

Referral channel
Data on lead referral channels should be analyzed to see which ones are the most effective and provide the most potential leads. Referral channels can be for example email newsletter, social media page or Google search.

Website visits

The frequency and time of the website visits in addition to the information of the specific pages visited is a good indicator for lead quality. For example a potential customer who has visited website's pricing page is most likely quite long in the buying process and makes him/her a very promising lead.

Call-to-action taken

Typically becoming a lead requires completing a call-to-action in a website, for example filling out a form. Type of the form and call-to-action can be an indicator of the lead quality: requesting a call or a demo could generate higher quality leads than just downloading a whitepaper.

Form responses

Often the forms include questions related to the company size and industry which can be used to recognize high quality leads.

4.5 Cases

Case ServiceMaster Solutions: Local B2B marketing

The case was described by Kirkpatrick (15 August 2012) in Marketing Sherpa research institute's repository of case studies on lead generation.

ServiceMaster Solutions was one of the biggest commercial facility cleaning franchises in the United States in 2012. As the company sells local services to businesses they had reached limit in building relationships with the traditional methods.

Even for a local service provider digital channels were an effective way to find new customers. When starting the digital initiative ServiceMaster had only basic web presence without a strategy for digital marketing.

A new website for the company was launched and after that search engine optimization and pay-per-click advertising were used as lead generation channels to attract visitors to the site. The new digital marketing program generated new incoming leads to ServiceMaster. Their website offered the visitor options to fill out a form or call to ServiceMaster directly.

Due to nature of the industry people more often preferred to call than wait for the company to respond after filling out the form. This required some special attention so that the leads were handled correctly. Digital tracking could be implemented fairly easily but tracking leads from the phone calls required manual work.

Results from the marketing program were very positive, including for example:

- Lead generation increased 150 % from 2010 to 2011
- Search engine optimization provided 1,500 % ROI in 2011
- Pay-per-click advertisement provided 200 % ROI in 2011

Case Managed Maintenance: Marketing automation and CRM

The case was described by Kirkpatrick (29 May 2013) in Marketing Sherpa research institute's repository of case studies on lead generation.

Managed Maintenance is a professional management services provider for technology assets. The company had already taken digital channels in their marketing strategy and utilized both marketing automation and CRM software. The challenge was that the solutions were separate and not sharing data.

The problem was solved by replacing both solutions at the same time while ensuring the new solutions were integrated and able perform the key tasks. This helped to align marketing and sales operations for example by giving greater transparency and data visibility to the salespersons.

The new solutions also provided marketing opportunities in the form of lead scoring and lead nurturing programs. New lead scoring program used several different criteria, explicit like industry and company size and implicit like email opens and clicks or website visits. The different criteria are assigned a point value. When a prospect has reached a defined lead score limit a sales opportunity is created directly in to the CRM system. In the CRM solution the salesperson can indicate that he/she doesn't think the lead is ready for sale and lead is sent back to marketing for lead nurturing.

After the new solutions were taken into use, lead generation increased 75 % over the previous year while at the same time share of the technology solutions from the marketing budget decreased. 30 % of new business in 2012 was run through the marketing automation solution.

5 Predictive analytics

Predictive analytics is a form of advanced analytics and can be defined as a blanket term for predicting future trends, events and behavior by applying machine learning algorithms and statistical analysis techniques. Predictive analytics process is based on an algorithm that analyzes current and historical data in order to predict future behavior or activity. Typically the output is a score or code indicating the likelihood of future behavior or event. (Leventhal 2018, 4-6; Kandarp 30 June 2017.)

Analytical modelling is usually split to two different types: prescriptive and descriptive. Prescriptive model tries to predict predefined target variable for each object. Typical use case of prescriptive model are campaign response models that can be used to predict if customer will renew their order. (Leventhal 2018, 8-9.) On contrary to prescriptive models, descriptive models are not restricted by any predefined outcome. Often these models are more strategic, typical use case for descriptive model could be dividing customers into segments. (Leventhal 2018, 11.)

There are many different machine learning algorithms that can be used in predictive models. The choice of algorithm should be made based on the required output from the model: is the analytical model prescriptive or descriptive. Machine learning algorithms can be categorized similarly into three different categories: supervised machine learning, unsupervised machine learning and reinforcement learning. (Bell 2014, 3.)

5.1 Supervised machine learning

Supervised learning algorithms use labelled training data to calculate output. Every data set in the training data will have both input and output objects. (Bell 2014, 3.) Supervised learning algorithms concentrate on finding a relationship between the output and input in the training data. Using the findings from the training data the algorithm will use this to predict output for new data sets. (Gollapudi 2016.)

Four widely used supervised learning algorithms are presented in more detail in this chapter: Bayesian networks, decision tree, random forest and support vector machines.

5.1.1 Bayesian networks

Bayesian networks uses a graph containing nodes and arcs to define the relationships between causes and effects. Each of the nodes in the graph contains the probabilities of the different outcomes and the arcs explain the relationships between them. When data is entered into the network, outcomes can be predicted based on the nodes' probabilities. As the nodes are connected, the resulting value in one node will affect the output probability of another node. (Bell 2014, 69; Leventhal 2018, 81.)

Practical example of Bayesian network can be seen in the Figure 3 where there are three different diagnoses for a patient: tuberculosis, lung cancer or bronchitis. The probabilities for the different diagnoses are recalculated as more insights on the patient are revealed.

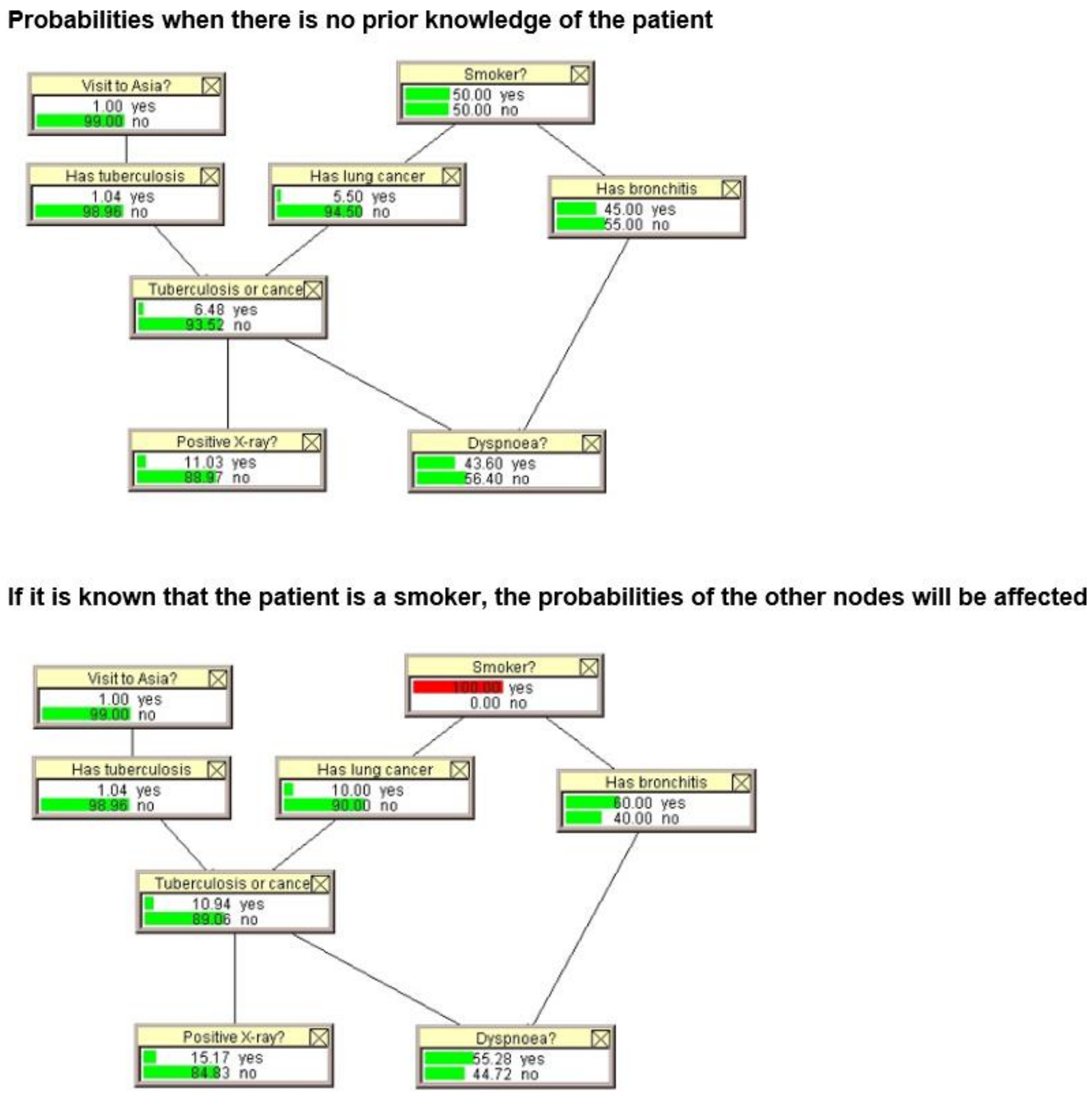


Figure 3. Bayesian network in a diagnostic example (Vomlel 2005)

5.1.2 Decision trees

Decision tree is formed of nodes and each of the nodes is associated with one input variable. The edges going out from the nodes are the possible values of that node. Decision trees start with a root node and end on a leaf (end node). End node illustrates the output which is calculated using the values given from the input variable in the path from the root node to the end node. (Bell 2014, 48.)

The decision tree algorithm uses the training data set to figure out which variables are the most important. The most important variables are placed at the top and towards the end nodes the variables come less significant. (Brink, Fetherolf & Richards 2016.)

Figure 4 displays a decision tree that is used in a loan decision. The root node in the tree is “Age” and it has two edges coming from it, whether the customer is under 55 years or older than that. The age of the customer impacts what happens after that. If the customer is under 55 then the model is requiring the information is he/she is a home owner. If the client is older than 55 then information about the customer’s credit rating is required. (Bell 2014, 49.)

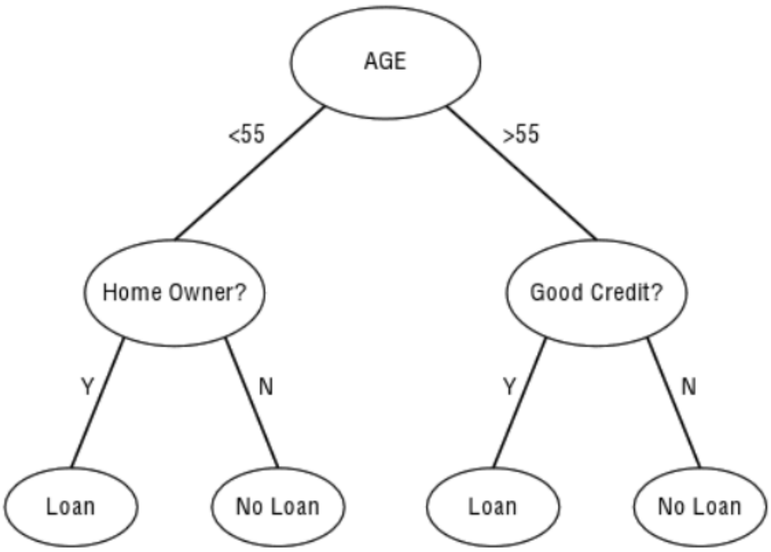


Figure 4. Example of a decision tree for loan decision (Bell 2014, 48)

5.1.3 Random forest

Decision tree introduced in the previous chapter is also the basis of random forest algorithm. Known issue with decision trees is that the top nodes of the tree have a very large impact on the output. Especially if the new data does not have the same distribution as the training data, the model's ability to make generalizations might be limited. (Brink & al. 2016.)

Random forest algorithm solves this issue by creating a set of decision trees to reduce the risks described earlier. Variables that are used in splitting are randomized in order to reduce correlation between the variables. The outputs of the decision trees are combined and the final output from the random forest can be calculated either by majority vote (in classification case) or mean (in regression case) of the decision tree outputs. (Brink & al. 2016; Dean 2014, 106.)

5.1.4 Support vector machines

Support vector machine is a technique for object classification. It is especially useful for more challenging cases where there are many types of classes. Support vector machine can be visualized as two or three dimensional plot with each object located within and every object is a point in that space. (Bell 2014, 139-140.)

In two dimensional settings support vector machines work as classifiers that define a line that separates the different classes in the best possible way. If there are more than two dimensions, the separator is a hyperplane in that space dividing the objects to classes. (Song 20 February 2018.)

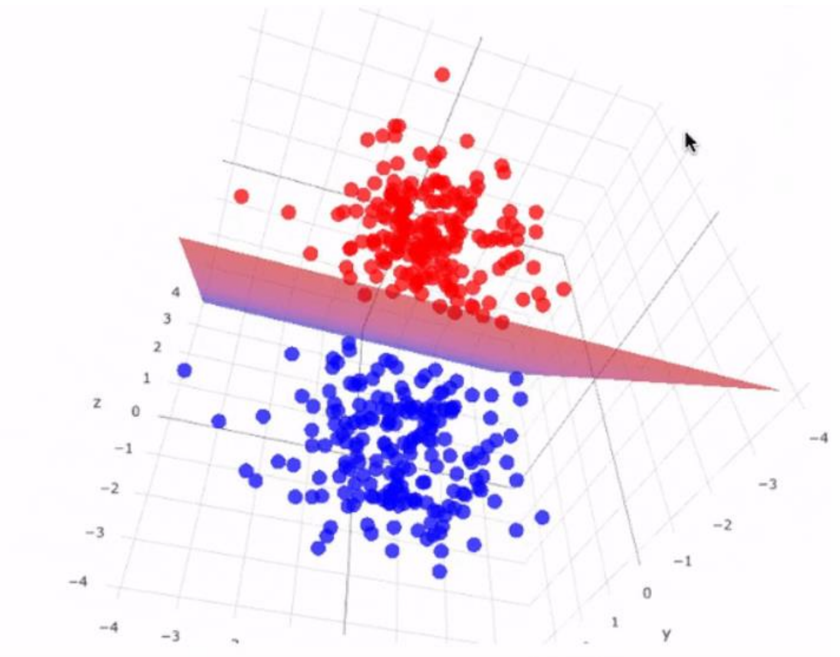


Figure 5. Visualization of support vector machine (Song 20 February 2018.)

Support vector machines are utilized in many different classification tasks, typical examples are pattern and image recognition as well as text classification. Also other fields like medical science are using support vector machines for example for classifying proteins. (Bell 2014, 140.)

5.2 Unsupervised learning

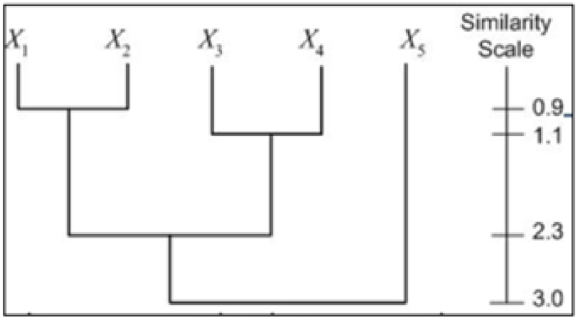
Unsupervised learning is based on algorithm finding a pattern in the unlabelled input data (Bell 2014, 3). This means that the algorithm learns from examples without any associated responses allowing the algorithm to find out the data patterns on its own. Unsupervised algorithms are able to provide useful insights into the meaning of data and also generate new inputs that could be used in supervised machine learning algorithms. (Mueller & Massaron 2016, 169.)

Two widely used supervised learning algorithms are presented in more detail in this chapter: clustering and association rules.

5.2.1 Clustering

The goal of clustering is to organize a group of similar objects from the given data (Bell 2014, 161). Classified patterns are found without any prior classification and the results of the clustering may vary depending on how the initial center points were selected. There are two types of clustering algorithms: hierarchical and partitional algorithms. (Gollapudi 2016.)

Hierarchical clustering algorithms focus on finding clusters that are hierarchical: either by dividing a large cluster to a smaller ones or combining small clusters into a larger one. The hierarchy of clusters can be represented as a dendogram or a Venn diagram which are shown in Figure 6. (Gollapudi 2016.)



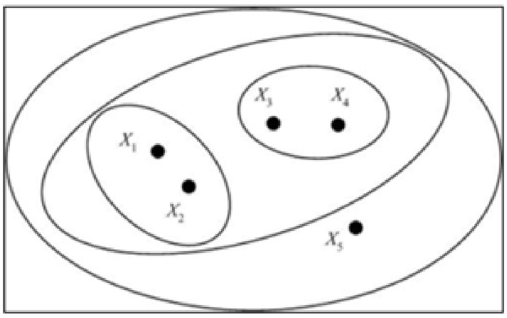


Figure 6. Representations of hierarchical clustering: dendogram on the left and a Venn diagram on the right (Gollapudi 2016)

Partitional clustering algorithms use predefined domain specific criteria to generate the clusters. There is no hierarchy between the clusters as they are mutually exclusive. Unlike hierarchical clustering, partitional clustering algorithms require an input that defines the number of required clusters. Commonly used partitional clustering algorithm is k-means algorithm where k indicates the number of expected clusters. (Gollapudi 2016.)

Cluster analysis is used in several areas of our daily lives: in digital applications in the form of social media network analysis in order to target advertising, in business they are widely used by market research companies and even in law enforcement to predict future crime locations and times. (Bell 2014, 162-163.)

5.2.2 Association rules

Association rules learning is used to find patterns and associations between objects as well as the transactions that resulted in a correlated result. An association rule represents a pattern that describes the probability of an event based on occurrence of another event, helping to find out relationships between objects often used together. (Bell 2014, 117; Gollapudi 2016.)

The aim is to find all the sets of objects that have greater support than minimum support using the dataset to predict the rules that have confidence greater than the minimum confidence. Typical example of the association rule is the market basket example: if a customer buys product X, he or she is likely to buy product Y as well. (Gollapudi 2016.)

Typically association rules learning is used for examining transactions, like point-of-sales systems data or web usage data. Web usage data can be used for example to suggest pages to users that they might be interested in to keep a website more compelling. (Bell 2014, 117-118)

5.3 Neural networks

Neural networks can be used in both supervised and unsupervised learning. They are based on a simple form of inputs and outputs (Bell 2014, 91). The core algorithm in neural network is the neuron. Neurons can receive several weighted values as inputs, sum them and provide a result based on the calculation. (Mueller & Massaron 2016, 280.)

Neurons are arranged in an interconnected structure that forms the neural network: each neuron is linked to the inputs and outputs of other neurons. Depending on the neuron's location in the network it can receive input features from the results of other neurons. (Mueller & Massaron 2016, 280.)

Neural network is structured differently than other algorithms: instead of having a fixed pipeline defining how data is received and processed, neural networks require fixing numbers of neurons and distribution to layers to define the information flow. (Mueller & Massaron 2016, 281.)

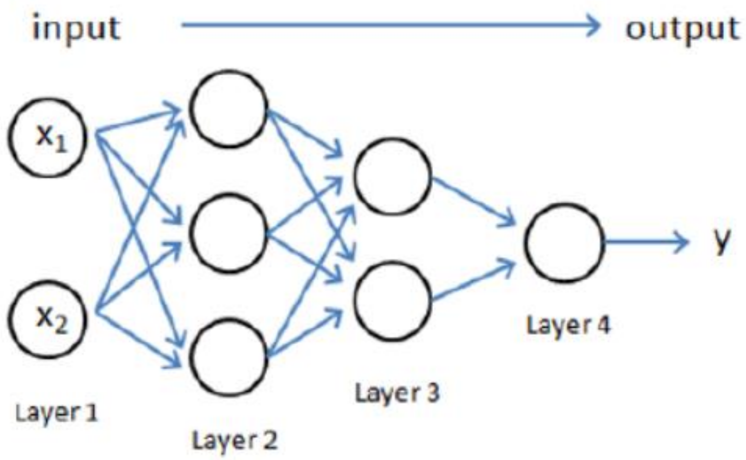


Figure 7. An example of the architecture of a neural network (Mueller & Massaron 2016, 282)

Neural networks are used in scenarios where data volume and speed is essential. Use cases include credit applications, robotics and medical monitoring. (Bell 2014, 92-93.)

5.4 Reinforcement learning

Reinforcement learning process starts similarly to unsupervised learning: unlabeled data is provided as an input into the algorithm. Based on what the algorithm proposes a positive or negative feedback is provided. (Mueller & Massaron 2016, 169.) Reinforcement learning is commonly modeled as a Markov Decision Process as seen in Figure 8.

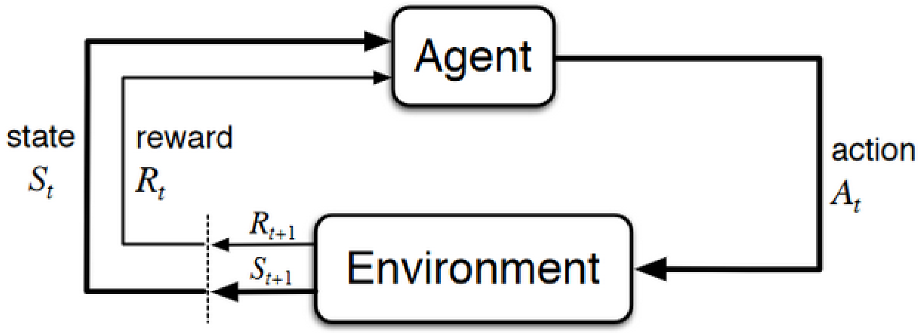


Figure 8. Markov Decision Process (Sutton & Barto 2018, 48)

Reinforcement learning focuses on maximizing the rewards from the provided results. The algorithm receives a periodic reward based on the made decisions. The results from reinforcement learning may require several steps to be executed before a result. The goal is that by exploring the data algorithm is able to generate a sequence of decisions to achieve the highest reward. (Gollapudi 2016.)

Reinforcement learning faces the challenge of making a trade-off between exploration and exploitation. The reinforcement learning algorithm prefers actions that it has found to be successful in the past in order to achieve the highest reward. But in order to find those actions the algorithm needs to try actions that have not been tested before. So a balance between the two activities must be found in order to succeed. (Sutton & Barto 2018, 3.)

Applications of reinforcement learning can be seen in several domains: games, computer cluster resource management, traffic light control, robotics as well as personal recommendations and digital advertisement bidding. (Towards Data Science 2 August 2018.)

5.5 Testing predictive models

When using predictive models in real business cases testing is a controlled way to introduce the different strategies: testing helps to understand the effects of the models and manage the possible risks. Testing predictive models contains three stages:

1. Designing the experiment to test the changes.
2. Composing a test sample, running the experiment and measuring the results.
3. Interpreting the results and making conclusions.

(Leventhal 2018, 207.)

When testing requires composing a sample from a population, it is possible that the observed change would have occurred only due to a sampling error. In statistical hypothesis testing, the result from the test is statistically significant when it is very unlikely to have occurred by chance. (Wikipedia 2018c.)

Statistical significance is used to determine if the null hypothesis should be rejected. The hypothesis to be tested is null hypothesis H^0 and the alternative hypothesis H^1. Typically null hypothesis is a statement that there is no effect or difference. Alternative hypothesis is tested against that, stating that there is an effect or difference. (Wikipedia 2018a; Wikipedia 2018c.)

P-value is the probability of observing an equal or more extreme effect or a difference assuming that the null hypothesis is true. If the p-value of the observed change is less than the defined significance level for the test, a conclusion can be made that the results reflect the whole population and the null hypothesis can be rejected. The significance level for a test should be defined before data collection. Depending on the field, the significance level is typically set to 5 % or less. Other commonly used levels are 1 % and 0,5 %. (Wikipedia 2018b; Wikipedia 2018c.)

The test for statistical significance can be computed either as one-tailed test or two-tailed test. The one-tailed test is appropriate if the alternative hypothesis specifies that the predicted value difference to the reference value is directed to one direction. In two-tailed test the difference with the reference can be in either direction. (Wikipedia 2018c.)

In a one-tailed test the region for the defined significance level is placed to one end of the sampling distribution and in two-tailed test the defined significance level is split to both ends of the distribution. Due to this on-tailed test is more powerful if the assumed direction of the alternative hypothesis is correct. Differences in the one-tailed and two-tailed tests is illustrated in Figure 9 and Figure 10. (Wikipedia 2018c.)

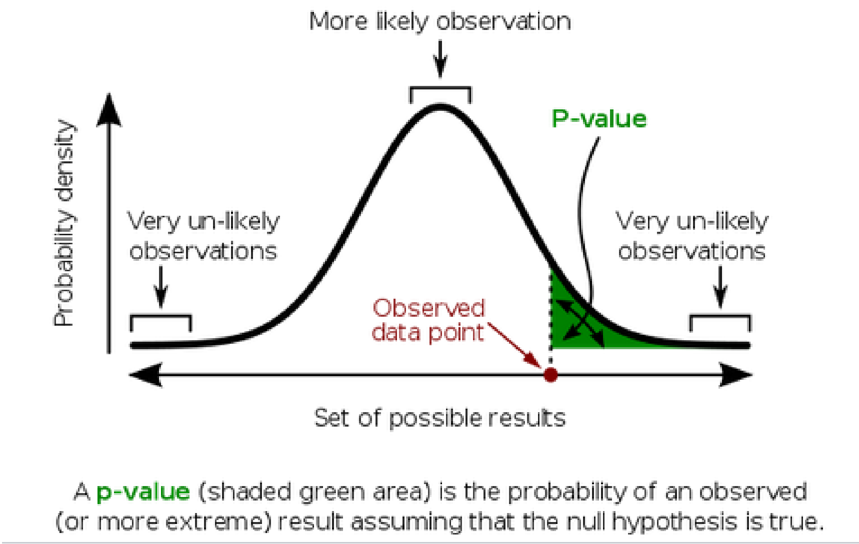


Figure 9. Example of a p-value computation in one-tailed-test (Wikipedia 2018b)

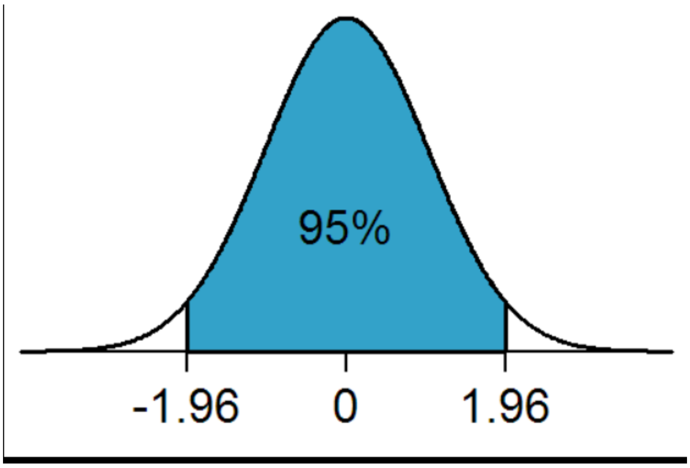


Figure 10. Example of a two-tailed test where the significance level of 0,05 is split to both ends of the distribution (Wikipedia 2018c)

6 Predictive analytics in marketing

For the purpose of marketing, predictive analytics if often used to predict the behaviour of an individual customer or group customers together so that they are actionable and meaningful for marketing. Predictive analytics can be used for example to predict what and when a customer is going to buy next or recognize different types of buyers based on the purchase data. Marketers can use this data to recommend certain products to customers proactively. (Artun & Dominique 2015, 24-25.)

Artun and Dominique (2015, 25) outline the following three use cases of predictive analytics in marketing:

1. Unsupervised learning is used to find hidden patterns in data. Unsupervised algorithms are typically used expose the underlying segmentation of the data, for example by finding groups of similar customers in the customer base without knowing in advance what kind of segments exist.

2. Supervised learning is used to estimate an output when given an input, by training the algorithm with sample inputs and target. Example of a use case of supervised learning is predicting product or service a customer is most likely to buy next.

3. Reinforcement learning leverages hidden patterns and similarities in the data to predict for example the best next steps or products for a customer. Reinforcement algorithms are most typically used for recommendations. Reinforcement learning is an option for the supervised learning case especially in cases where no labeled training data set is available.

Leventhal (2018, 9-11) uses slightly different categorizations to predictive and prescriptive models. Predictive models are similar to supervised learning where the model is designed to give out a particular output. Tables 1 provides examples of marketing applications of predictive models and the related business questions.

Table 1. Examples of use cases of predictive models in marketing (Leventhal 2018, 9)

Application	**Question**
Customer selection from prospects	Which prospects are most likely to buy?
Cross-sell and up-sell campaigns	Which existing customers of a particular product are the most likely to buy another product or buy more of the particular product?
Next Best Offer	Which product customer is likely to buy next?
Customer retention	Which customers have the highest likelihood of lapsing?
Customer lifecycle management	How long it will take for the customer to likely lapse?
Win-back campaign	Which of the former customers are most likely respond to a win-back campaign?
Customer lifetime value	What is the predicted future value of purchases for customers?

Prescriptive models is an umbrella term covering unsupervised learning and reinforcement learning where no output is designed beforehand. Examples of marketing applications of prescriptive models and the related business questions are listed in Table 2. (Leventhal 2018, 11.)

Table 2. Examples of use cases of prescriptive models in marketing (Leventhal 2018, 11)

Application	**Question**
Customer segmentation	What are the factors explaining differences between customers?
Customer segmentation	How can the customer base split into groups that are relevant for marketing?
Product affinities	What are the products that are more likely to be bought together?
Product recommendations	If a customer buys a particular product which other products are the buyers of that product also likely to buy?

6.1 Clustering models

Clustering models is an approach that uses unsupervised learning to find similarities in the group of customers without defining any hypothesis of these groups beforehand. The pattern of group of customers who behave in a similar way would emerge from the data using a clustering algorithm. A simplified example of such cluster could be customers who only buy when they receive a discount. (Artun & Dominique 2015, 25.)

Usually 8 to 15 different attributes are required to define a customer cluster. Relevant customer attributes could be such as age, gender, location, time of purchase, type of purchase, price sensitivity or if they buy from the store or online. Traditional methods for defining customer segments have typically been based on assumptions and human intuition. Using clustering algorithms can help to automatically find statistically significant groups of customers. These findings from the clustering algorithm can be turned into buyer personas that can be utilized in different marketing strategies for these groups. (Artun & Dominique 2015, 27-28.)

A clarifying example could be for example sunglass buyers. This segment can actually consist of two clusters: one cluster could be women going for vacation and the other cluster could be passionate runners. This knowledge would be valuable when defining the marketing strategy and messages for these groups instead of approaching all sunglass buyers with the same message. (Artun & Dominique 2015, 28.)

It is important to acknowledge that a person never belongs to only one segment – this is often the biggest mistake made by marketers. The segment of the customer can depend on the situation as segments are very contextual. (Artun & Dominique 2015, 100.)

Clustering can be used in marketing in different ways: some approaches are product based clustering, brand based clustering and behaviour based clustering. Product based clustering models define clusters based on the knowledge of the type of products they buy and what are the products that are often bought together. (Artun & Dominique 2015, 95).

Brand based clusters predict the brands customers are most likely going to buy. Customers who prefer some brands more than others are group together. The brand based clusters can also reveal customer’s interest to other related brands by comparing customer’s preference with an existing brand cluster. In retail world brand clustering is especially relevant as many retailers have discovered that customers’ affection with brand is often stronger than with products. (Artun & Dominique 2015, 95.)

Behaviour based clustering model uses purchase behavior to group customers together. Relevant data points could be for example the amount of money spent, how often the customer buys, how frequently customer buys, order seasonality or if the customer is keen on discounts. Different marketing approaches can be used with these above mentioned groups. Customers who are after discounts can be targeted with marketing for inventory-clearing sales or high spenders with preview of a new product line. (Artun & Dominique 2015, 97.)

6.2 Propensity models

Propensity models use historical data to make predictions about customer's future behaviour. They can be used for example to predict how likely a customer is going to buy a particular product, how likely a customer is to engage with the company's website or what is the customer's predicted lifetime value. Propensity models are very commonly used in direct mailings to predict if customer is likely to buy after they have received a mailing. (Artun & Dominique 2015, 29; Strickland 6 January 2015.)

Propensity models could also be used in retargeting campaigns for customers who had visited the company website but did not convert to sale or a lead. The offer in the retargeting campaign could be personalized based on the customers' likelihood of buying: with customers who have very low likelihood of buying might need a discount to be interested and on the other hand customers' with high likelihood of buying might just need a reminder of the product or the brand. (Artun & Dominique 2015, 30.)

For first-time buyers non-transactional data can be used to predict their likelihood to make a first purchase. Non-transactional customer data can be for example how the customer behaves on the website or how many times the customer clicked on an email. Also demographic data can be used to compare the prospective buyers with other likely buyers. In consumer marketing these can be for example age or gender and in B2B marketing relevant demographics could be geography, industry or the person's job title. (Artun & Dominique 2015, 124.)

The prospective buyers who behave similarly with the previous buyers can be identified with high likelihood of buying and can marketed accordingly to help to close the sale. Knowledge of customer's likelihood of buying can also be used to prioritize marketing investments for the prospective customers. (Artun & Dominique 2015, 124.)

When a customer makes their first purchase already information about that purchase combined with demographic, geographic and engagement data can give a prediction on the customer's lifetime value when compared with other historical customer data. The predicted lifetime value could be used for well-founded marketing decisions, for example to focus investments on those marketing campaigns and channels which generate customers with the highest lifetime value. (Strickland 6 January 2015.)

Propensity model can also be used to analyze which customers should not be contacted - one form of this is an unsubscribe model. With a propensity model it is possible to predict how likely customer is to unsubscribe from a mailing list at any given time. This information could be used to adjust the sending frequency based on the customer's likelihood to unsubscribe or choose another channel than email for the customers with high likelihood of unsubscribing, especially if those are high value customers. (Strickland 6 January 2015.)

6.3 Reinforcement learning and collaborative filtering

In marketing applications reinforcement learning is often used together with collaborative filtering models. Collaborative filtering models are typically used in recommender systems. Recommendation models utilize collaborative filtering, Bayesian networks and frequent item sets to make predictions. Also time-decay functions are utilized to give recent behaviour more weight than older behaviour. After customer recommendations are generated, reinforcement learning is applied to teach the model about the customer's preferences. (Artun & Dominique 2015, 33.)

Recommendation models can be used in suggesting interesting products or content to the customers. Product suggestions will help to increase value of the customer and drive revenue. Content recommendations often have more indirect effect in form of increasing brand engagement, loyalty and customer satisfaction. (Artun & Dominique 2015, 33.)

Presenting the recommendations in the right context is very important so that they don't feel disturbing or intrusive. They should also be used at the relevant time in the customer journey. Before the purchase is completed often a recommendation of type "customers who bought this, also bought…" is made to the customer in order to increase the order value. Few days after the purchase a thank you mail could include some additional recommendations based on the purchased products. (Artun & Dominique 2015, 33.)

It is recommended to be as transparent as possible with the customers about the recommendations and offer explanations how they were calculated. This will help to reduce the intrusive feeling some customers might get from receiving recommendations on products or content. The recommendations should be updated as often as possible, ideally in real time in order to stay relevant. Good recommendation model also allows manual tweaking of the algorithm for example to exclude certain products that have bad reviews or products that are out of stock. (Artun & Dominique 2015, 33-34.)

6.4 Case: Micro-segmentation of business mobile subscribers

Leventhal (2018, 178-179) describes a use case of predictive analytics in micro-segmentation of business subscribers of a mobile phone operator. The mobile phone operator had traditionally segmented their business customers based on the way the customers were managed. The company wanted to have more understanding of the different types of mobile users and their needs among their business subscribers.

The company made a hypothesis that the segmentation that was done on their consumer subscribers would be a good foundation also for the business subscribers. To test the hypothesis the same variables as in the consumer segmentation were assigned to the business users and a clustering algorithm was used in order to map the business users to the most relevant consumer cluster. Most of the business customers were a good fit for the consumer cluster they were assigned to, yet some did not fit the existing consumer segments. Based on that additional segments were identified among the corporate and SME companies.

The segmentation allowed the company to assign all business subscribers to usage segments and investigate the segments within industry, market segment or business accounts. The usage segments could be utilized in several areas of the company’s operations, including channel and customer management, sales as well as proposition management.

7 Implementation

7.1 Current lead process and use of predictive analytics

In Fonecta's lead generation strategy several different touchpoints are used to generate leads in the digital channels, including digital advertisements, social media, email marketing, search engine optimization and campaign landing pages.

The different channels are utilized to attract traffic to the company website or campaign landing pages. The website or landing page visitors can be qualified as a sales lead based on their actions: filling out a contact form, downloading an e-book or clicking on a certain link in a marketing email.

When a visitor performs a specified action on the website or landing page a trigger is sent to the marketing automation system with the details on the performed actions. Based on predefined rules the marketing automation system can qualify the visitor as a lead.

If the visitor is qualified as a lead the details of the visitor and performed actions will be sent to the CRM system which is used by the sales personnel. Predefined rules define if the lead should go through the analytics solution which will make a prediction on the best sales representative to handle the lead. A simplified presentation of the lead generation process is illustrated in the Figure 11.

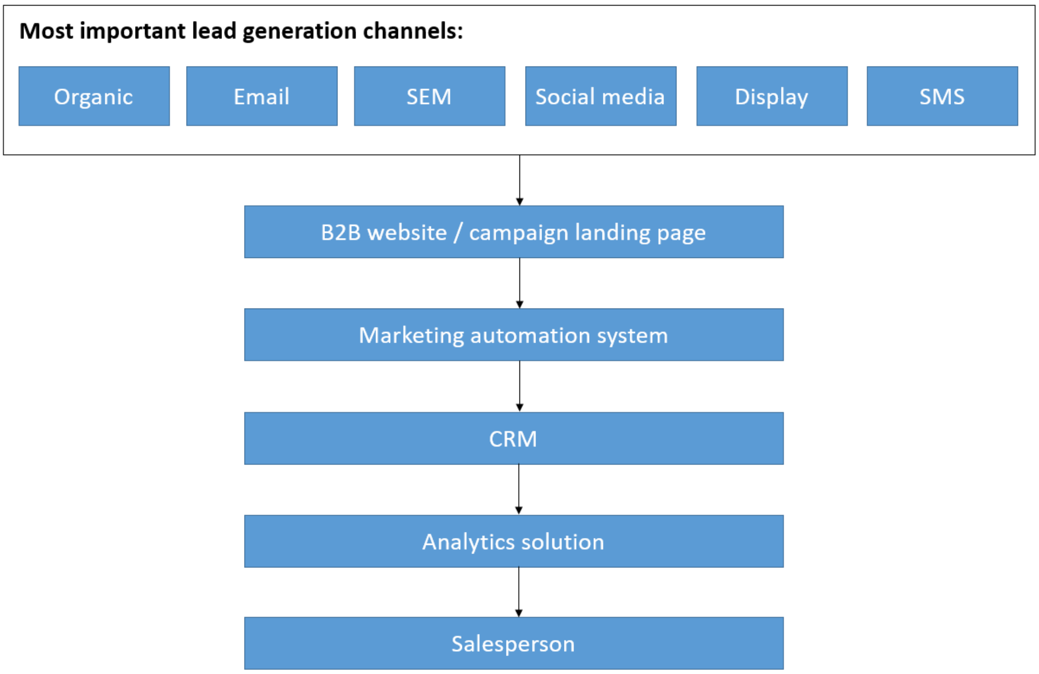


Figure 11. Fonecta's lead generation process

7.1.1 Predictive analytics in lead generation channels

Three of the lead generation channels illustrated in Figure 11 utilize predictive analytics in some form: email marketing, SMS and Facebook advertisements.

Email and SMS target groups are selected based on a predictive model used to define Next Best Offer (NBO) for a particular customer. Based on the NBO predictions the customers are assigned into target groups for email and SMS campaigns so that they can be addressed with relevant product offerings. Some of the email target groups are defined based on hard rules instead of NBO predictions. The actual NBO predictions are used in email campaigns of three of Fonecta's products: Google AdWords, Websites and Company Profile.

The model used in email and SMS campaigns uses supervised random forest algorithm in order to find the most relevant variables from customer data which might indicate company's willingness to buy the product. It uses several variables in the training data such as firmographic information (e.g. revenue, personnel class and company type), Net Promoter Score, customer care cases, use of Fonecta's consumer services (Fonecta Caller) as well as the technical website quality of the company.

Predictive analytics is used in Facebook advertisements in several ways for selecting correct audiences for the advertisements. Facebook does not disclose the algorithm they are using in their advertisement solutions. The different use cases in include:

1. Email target groups containing the NBOs are loaded into Facebook and used for targeting advertisement for people who also received the email.
2. Targeting advertisement to a lookalike audience of the people who have received the email (described in the previous bullet).
3. Targeting advertisement to a lookalike audience of people who have visited Fonecta's B2B website.
4. Targeting advertisement to a lookalike audience of people who had completed the advertised action (for example completed a test on the website or downloaded an e-book).
5. Targeting advertisement to an audience based on the content and articles consumed on Fonecta's B2B website

Organic, Search Engine Marketing (SEM) and Display advertisement channels do not currently utilize predictive analytics methods.

7.1.2 Analytics solution

After the lead is created in the CRM system it is inserted into a workflow. The workflow has predefined rules which define if the lead should be assigned to a salesperson manually or if it should go through the analytics solution.

The analytics solution uses a Multi-Armed Bandit algorithm to predict to which salesperson the lead should be assigned to. The algorithm uses historical data of the won and lost leads for that salesperson for specific products. The purpose of the algorithm is to calculate which salesperson from the available pool would be the most successful in closing a sale for that lead.

7.2 Creating the predictive model

Email campaigns using the NBO modelling were selected as the pilot use cases for this study. The reasoning behind this selection was mainly due to the large volume of the email communications which made possible to gain relevant amount of data from the pilots in a relative short time frame.

The NBO model used in the campaigns is based on random forest algorithm which is a supervised machine learning method. The training data contains several types of variables (not just numerical) which makes random forest a good choice as it does not require separate input preparation as it can take in also categorical data. Using random forest instead of simple decision tree will also reduce the risk of overfitting the model. The NBO predictions are run on a weekly basis for the whole customer base so the selected algorithm needed to be fairly efficient and fast.

The training data of the existing NBO model was modified considering three different aspects:

- Freshness of the data. Old model used data starting from 2014. New model uses data gathered 2016 onwards.
- Relevancy of the data. Old model used only data from sales calls. New model combines sales call and lead data.
- Due to organisational restructuring data about calls to the directory assistance service could not be used as an attribute in the new model.

Other aspects of the existing NBO model for the email campaigns were left as before.

Before lead data was integrated into the predictive model a clean-up and classification process was carried out. If the lead had been closed for particular reasons, for example lead expired or not contacted, they were not taken as part of the training data as they could not be labelled as neither lost or won leads because sales negotiations never took place. Also rules for defining which lead statuses should be labelled as lead won and which lead lost were defined. Table 3 defines the different lead statuses and how they were categorized for the predictive model.

Table 3. Lead statuses and the categorisations for the predictive model.

Lead status	**Categorisation**
Qualified	Lead is categorized as won
New sales call is linked to the company	Lead is categorized as won if the linked sales call is won
Pending sales call is linked to the com-pany	Lead is categorized as won if the linked sales call is won
Pending sales call or opportunity is linked to the company	Lead is categorized as won if the linked sales call or opportunity is won
Opportunity exists	Lead is categorized as won if the linked opportunity is won
Customer did not want to buy	Lead is categorized as lost
Not relevant for the customer	Lead is categorized as lost
Customer care case	Not included in the model
Expired	Not included in the model
Not eligible for contact	Not included in the model
Own lead converted to sales call	Not included in the model
Sales person has left the company	Not included in the model
Status not available	Not included in the model
Was not able to reach the customer	Not included in the model

Classification of the data to particular products was needed in order to map it to the existing attributes in the model. Classification of the lead data was carried out based on the campaign codes and subject lines of the leads.

When starting the pilot with the new model the training dataset consisted of 250 000 sales calls and 22 700 leads in the training dataset.

7.3 Pilot use cases

The new predictive model was used in target group selection for 5 different email campaigns. The email campaigns featured three different products that utilize the NBO prediction in the target group selection. The target groups for these campaigns contain companies from the SME segment. Some details on the campaigns are described below.

Campaign 1
Company profile campaign. Call-to-action in the email is to get the customer to check how the company's profile look in Fonecta's services.

Campaign 2
Google AdWords campaign. Call-to-action in the email is to get the customer to ask for a recommendation for the best search phrases in Google AdWords for his/her company.

Campaign 3
Website campaign. Call-to-action in the email is to get the customer to check the quality of his/her company's website and receive information on the average quality of websites in that industry.

Campaign 4
Company profile campaign, targeted for customers who have been also assigned for sales call. Call-to-action in the email is to get the customer to check how the company's profile look in Fonecta's services.

Campaign 5
Google AdWords campaign, targeted for customers who have been also assigned for sales call. Call-to-action in the email is to get the customer to ask for a recommendation for the best search phrases for Google AdWords for his/her company.

8 Results and validation

Number of emails delivered and number of email clicks was used to run the significance tests for the pilot case results. The number of opened emails is a fairly unreliable metric for engagement as it is dependent on the respondent downloading images in the email in order to trigger a tracking pixel.

Calculations for statistical significance were conducted with A/B testing significance calculator provided by AB Testguide. The test evaluation was done with two-sided hypothesis and 95 % confidence. Two-sided test was selected in order to show evidence if the new variation of the predictive model had improved or decreased the email engagement metrics when compared with the email engagement metrics with 2017 version of the model.

The email engagement metrics show that none of the pilot campaigns had any statistically significant improvement in email engagement during the pilot period. The results are displayed in more detail in Table 4.

Table 4. Email statistics from the pilot campaigns (1 September – 31 October)

Campaign	**2017**			**2018**			**P-value**	**Significance**
	Delivered	Opens	Clicks	Delivered	Opens	Clicks		
Campaign 1	14692	4891	348	13209	4254	280	0.9197	No
Campaign 2	6977	2382	182	6126	2069	147	0.7778	No
Campaign 3	4853	1580	167	4361	1433	122	0.9624	No
Campaign 4	3012	969	69	2949	903	48	0.9678	No
Campaign 5	2291	793	47	3612	1169	87	0.1804	No

Possible reasons for not being able to get statistically significant results can be due to the relatively short pilot period as well as the reason that the amount of lead data that was integrated into the predictive model was still relatively small compared to the amount of sales call data. Probably it will take a longer time to gather enough lead data in the training set in order to get statistically significant results from the campaigns.

Also changes in the lead hit rate during the pilot period was analysed. No clear trend was seen in the hit rate either, as the direction change varied from campaign to campaign. The changes in the hit rates were relatively small, from 1,7 % to 6,1 %. Details of the results can be seen in Table 5.

Table 5. Lead statistics from the pilot campaigns (1 September – 31 October)

Campaign	**2017**		**2018**		
	Total leads	Hit rate	Total leads	Hit rate	Change
Campaign 1	117	9,9 %	60	6,3 %	-3,6 %
Campaign 2	158	3,0 %	136	9,1 %	+6,1 %
Campaign 3	44	10,8 %	49	9,1 %	-1,7 %
Campaign 4	18	12,5 %	15	15,4 %	+2,9 %
Campaign 5	38	10,8 %	81	8,1 %	-2,7 %

The largest change was seen in Campaign 2 where the hit rate increased 6,1 % from last year. That might be a subtle indicator that this new model was able to generate more high quality leads. Yet it is important to keep in mind that he hit rate is influenced by many other variables (e.g. which products sales personnel is focusing on, number of sales representatives etc.) so no conclusions should be drawn based solely on that.

8.1 Recommendations for future

When starting the pilot with the new predictive model the training data consisted of 250 000 sales calls and 22 700 leads in the training dataset. So the number of lead data is still relatively small and therefore still has limited impact on the predictive model. Recommendation would be to continue to run the pilot cases which monthly checks on the significance of the results.

Another possibility would be to create a new model based solely on lead data to examine if the customers converting to a sale from lead instead of a normal sales call are different in some ways when considering predictive variables for the NBO model.

Based on the workshops some additional development ideas for use of predictive analytics were gathered. The most potential ideas for future development are described in short below.

Integrating information on customer's engagement with the emails to the current NBO model. At the moment the model does not take into account if the user has opened or clicked an email of that particular campaign or any campaign before. This kind of behavioural data would be very valuable especially in cases when the customer has no previous purchases.

Scoring customers based on if they had received 'value for money' for certain products. Value for money means here that the customer has received good results when the monetary investments on the product or service are considered. This could be from some aspect a similar indicator as the Net Promoter Score which is already included in the model, as this data could possibly give an indication on the customer satisfaction but most importantly it could also reveal which related products might be a good fit for the customer based on the previous results.

Integrating information to the current NBO model on how much clicks the company and the companies in the same industry have received in Fonecta's search services. This could be especially relevant for the NBO model for Company Profile product where the above metrics are important KPIs.

9 Conclusions

Objective for this study was to identify new ways of using predictive analytics in the lead generation process and study their impact in pilot use cases. This objective was partly reached. New development ideas for predictive analytics were generated during this study as stated in the objective.

The existing Next Best Offer (NBO) predictive model was modified for the selected pilot cases. In addition to sales call data, lead data was added to the analytic dataset which is used to teach the model. Lead data cleanup, preparation, categorization and formatting were carried out in order to integrate the data in the modelling software.

The results from the selected pilot cases did not have any statistically significant results that could have been used to evaluate the validity of the implemented predictive model. Answers to the specific research questions are discussed below.

RQ1: How are predictive analytic methods used in different parts of the company's lead process at the moment?

The current lead process flow was documented during this study as well as the predictive components in it. The documentation was done on quite high level as it does not go in specifics into for example how our different email campaign target groups are selected. One outcome of this study and the documentation of the current process was also that we identified the parts of the process that would need to be documented in more detail.

RQ2: How could use of predictive analytics in lead generation be improved?

Several improvement ideas on the use of predictive analytics were gathered during the study and one of them was selected to be implemented in the pilot cases. As email marketing is the most important individual channel in Fonecta's lead generation process, the ideas focused heavily on better utilization of predictive marketing in the NBO model which is used in the email channel.

RQ3: How can the results of the pilot use case be analyzed and reported?

The systems included in the lead process, marketing automation system and the CRM system, allowed us to analyze the results from the delivered emails up to the closed sale. All the results could be reported and analyzed in quantitative form and the statistical significance could be evaluated for relevant parts to validate the results. The analysis of the results was done focusing on the email statistics: customer engagement with the email was analyzed based on click-delivered ratio for the pilot cases.

RQ4: What are most promising use cases for future development?

Some future development ideas were generated during the workshops, most potential and relevant in the near future would be to include email engagement data (email opens, email clicks) as part of the predictive model. As discussed in the theoretical part of this study this type of non-transactional customer data can be valuable when building propensity models.

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