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# Capturing the effect of marketing campaigns through customer transitions

Student: Cecilia Norberg

Student ID number: 449919cn

Supervisor: Dr. V.G. (Vijay Ganesh) Hariharan

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## Abstract

Though there has been a major shift in marketing analytics towards using more statistically valid methods, there is still a major gap between what academia suggests and what is done in practice. In this thesis I look at the simple method of RFM segmentation and highlighting the importance of creating a strong customer base. Broadening the use of segmentation, direct marketing campaigns are applied with different sentiments attached to them. Hence, finding which campaigns affect which customers positively. Furthering on the impact of direct marketing campaigns, year on year transitions with the RFM scoring method is analysed along with looking at the maximum likelihood of transitioning under the hidden Markov model. Here I look at if the two can be used interchangeably or if they should be used to support one another. In the end both models have their own merit and though the RFM does not nearly provide as much information as the HMM, the RFM is a very good option for organisations who have yet to delve into the area of careful segmentation and who perhaps do not fully understand their customers. With the right tools and understanding the HMM can provide a wealth of information about one’s customers and their behaviour. The managerial insights of the research show the importance of segmentation so lower segments can be nurtured if they show potential. By retaining lower segments hopefully, one should be able to create a stronger base of major donors for the future. While keeping in mind to look more carefully at who should be contacted, thus limiting over exposure, and contact fatigue.

Keywords

Segmentation; Direct Marketing Campaigns; Non-Profit Organisations; RFM, Hidden Markov Model

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# 1 Introduction

***Consumers move between discrete phases of loyalty when the consumer-brand relationship is altered, for the better or worse (Oliver, 1999).***

The key issue being covered in this study, are the effect that different campaign sentiments have on different stages of customer loyalty. This is worthy of investigation as guidelines can be put in place to encourage organisations to put more emphasis on retaining their customers but also try and increase the customers lifetime value. Sargeant (2001b) found that even a small shift to improve the level of attrition can encourage a large improvement of the customer lifetime values of the database. Individuals commonly make small purchases from organisations as a result of an initial interaction and over time organisations can work to prove that they are worthy of this support to grow the relationship. Rosso (1991) states that in order to develop relationships with their customers and ensuring enduring relationships, organisations should be prepared to dedicate time and resources. Water (2011) support this idea by stating that as the relationship grows between the organisation and their customers, they should be able to pursue larger purchases. The goal of this study is to gain a greater understanding of the impact an organisation can have on these alterations, and ultimately move the customers to a greater plane of loyalty. This will be done by analysing the sentiments are associated with the different direct mail campaigns sent out and seeing the impact of each sentiment on the donors. The nature of this research is to look at two different methods of transition models and to see if the machine learning method hidden Markov model (HMM) suits this issue rather than the more commonly used econometrics model of recency, frequency and monetary value (RFM). The research will be conducted within one non-profit organisation (NPO) located in The Netherlands.

## 1.1 Background

The interest for this subject came about through the author's own personal interest in consumer behaviour and marketing analytics, which was enhanced throughout the Marketing Masters, and previous research positions at various firms. As the nature of marketing as a firm department has been changing in recent years, it would be great if this study is able to re-emphasise the importance of understanding an organisation's customers and seeing what drives them to make purchases.

## 1.2 Rationale

The study being conducted in a nutshell, is working towards ensuring that the right message is sent to the correct customers as to maximise profit and minimising contact fatigue. As, if a customer is found to be more likely to respond to certain sentiments or forces driving giving, the organisation can tailor the information sent to those customers. Therefore, as each customer is not sent each type of campaign, contact fatigue should be prevented. The stakeholder of this study are the managers/employees of a marketing department. What the stakeholders can learn from the study is how to appeal to the right customers, and thus tailor campaigns to specific segments. At the end of the study recommendations will be provided, educating the stakeholders how to segment their customers more carefully and teaching them to run the analysis for themselves to ensure that the information is kept up to date.

## 1.3 Research Problem

The problem being analysed in this study is looking into customer behaviour, in terms of customers transitioning between segments. Explaining customer behaviour when exposed to direct mail with different sentiments. The direct mailing campaigns that will be looked at are Contribution, which ask donors to become continuous, contractual, donors, Gift, which asks donors for a general donation to the organisation and Emergency Aid, which asks donors to donate to a specific cause. The independent variables that will be analysed are, three different direct mail campaigns, and the amount/average amount donated at each transaction, the frequency of donations and how recent was the last purchase. The goal is for the study to be generalizable, to any customer focused sector and not just the fundraising sector, which the data is based on. This study will add to literature as it be more general than the previous research conducted but also make research into segmentation and customer movement more approachable. This study contributes to the current knowledge of this topic will shift the focus to understanding the sentiments behind different direct mailing campaigns, rather than just looking at the goal of the campaigns. This will allow marketing departments to make more accurate predictions into what customers to invest more time and effort in. Though similar research has been done before in the form of the work done by Netzer et al., (2008), which provided a great deal of inspiration for the research at hand. The study will attempt to make contributions into the literature by analysing the boundaries of the current research and to see if the relationships found. Hence the aim becomes, to test for differences in future donating behaviour by analysing the effect of direct mailing campaigns with different sentiments on donors in a discrete-time setting.

In order to satisfy the research aim stated above, the following research questions have been identified:

1. What is the difference in donating behaviour of donors when exposed to the direct mailing campaigns with sentiments related to asking for contractual loyalty, one off donations and donations towards emergency causes?
2. To what extent will Contribution, Gift or Emergency Aid elicit a higher level of loyalty?

## 1.4 Academic Relevance

In order to highlight how this study differs from previous studies, the findings of the literature review will be analysed with an emphasis on how the study at hand makes contributions over and beyond those findings. When looking at the broad spectrum of relationship marketing, the literature suggested that there are two common ways in which studies are categorized. The studies following the perspective of consumer behaviour lead by Fournier in 1998 and, Fournier and Yao in 1997, and the empirical modelling perspective lead by Bolton in 1998; Bolton and Lemon in 1999. How this study differentiates is that these two perspectives will be merges as the behaviour of the donors will be analysed through empirical modelling, to track the changes in behaviour of the donors.

Next the topic of relationship marketing was looked at from the perspective of NPOs and their relationship with the donors. Here it was found that in the last decade there has been a shift in the focus of NPOs to behave more like for-profit organisations, and thus becoming more aware of the cultivation of major gift donors rather than just the emphasis on the value of the relationships within fundraising (Waters, 2011). Here the study will simply build on this new wave by enhancing the little focus there is on defining loyal customers through various means and growing these loyal customers. When looking at the mechanisms behind charitable giving, a focus is put towards the reasons why individuals donate and looking how these mechanisms relate to the decisions of the marketing department when choosing how to encourage donations. Hence rather than simply looking at if donors choose to donate or not, going deeper and seeing what causes individuals to make the donations (Bekkers and Wiepking, 2011). Further, the drivers will be analysed and applied to the campaigns to find what campaigns trigger what mechanisms.

The same is true for the section on relationship marketing activities. Here the literature focuses on the impact of various types of activities, rather than looking at the variations in sentiments that can be applied to these activities. As found by Dolnicar and Lazarevski (2009), most NPOs have an organisation-centred focus rather than a market-centred one, leading to a lack of focus into the wants and needs of the donors and what sentiments appeal to what customers.

When looking to the research previously done on the RFM model, there are various alterations. As found by Coussement et al., (2014), depending on the case at hand there needs to be modifications to the model to suit the needs of the research. Commonly within RFM research, the studied stop after the segmentation level, where this study will use those segments to conduct a transition matrix to see how those segments move from year to year.

For HMM models, most of the research conducted has had a focus on speech recognition, image recognition, finance and genetics. Little research has been made in the field of marketing, and often the research done has made strong alterations to the original model, such as Netzer et al., (2008). Hence, this study hopes to simplify the HMM model and make it more approachable to everyday use and to be used hand in hand with other analysis.

# 2 Theory

## 2.1 Literature Review

### 2.1.1 Introduction

The aim of the literature review is to situate the research for this study within a wider disciplinary conversation. Illustrating the importance of the research for the subject area of marketing. This section also aims at critically assessing the important research trends within traditional marketing and showcasing the difference to NPOs and their approach to marketing. As well as identifying potential gaps in the knowledge available.

### 2.1.2 Relationship marketing

The first step in this literature review is to look at the broader perspective of relationship marketing. Naturally within such a broad topic there will be different perspectives taken, the two that will be highlighted here were pioneered by Fournier, Yao, Bolton and Lemon. Leading the consumer behaviour perspective, which focuses on the importance of relationships from a consumer-organisation perspective and seeing the organisation as an active partner in this relationship. This idea was led by Fournier (1998) and was based on the research of Fournier and Yao (1997). What Fournier and Yao (1997) discussed was that not all consumer-organisational loyalty relationships are the same in terms of the strength nor character. They further discussed that even though the consumer might find that they are loyal, the organisation might not see it from the same perspective. Therefore, Fournier and Yao (1997) conclude that organisations need to begin to look at loyalty from the perspective that it plays a much larger role in the relationship rather being a separate entity.

Bolton (1998) and, Bolton and Lemon (1999) look at relationship marketing from the empirical modelling perspective. Where Bolton (1998) investigated the effect of time on customer relationship, by focusing on customer satisfaction and the role it plays. It was found in her work that the duration of the relationship depended on how positively or negatively the customer experienced the service whilst a customer. Accordingly, when either a positive or negative incident occurred, the current state of the relationship would be revealed Customers that have however passed a certain threshold in terms of years have found not to be affected by negative occurrences. This is because the prior positive interactions would out weight the more recent negative occurrences (Bolton, 1998). This notion is highlighted by Oliver (1999) who suggested that consumers move between discrete phases of loyalty when the relationship is transformed, causing either a positive or a negative reaction. Bolton and Lemon (1999), were able to build on Bolton's (1998) research and was able to quantify the relationship between customer satisfaction and service usage through the introduction of the perceived payment equity concept. This concept was able to capture the customer's changing evaluation of the fairness of the exchange, and thus see how a customer's usage levels could be managed through various pricing strategies, and communication means (Bolton and Lemon, 1999)

Relationship marketing can also be viewed from both a behavioural perspective and a managerial perspective. Where the behavioural perspective has mainly focused on understanding the link between the underlying dynamics of a relationship and the emotional dimensions of these relationships. With Dwyer, Schurr and Oh (1987), highlighting trust as an element of relationships that merge a sequence of interactions between the customer and the brand to form a long-term relationship. The managerial perspective on the other hand, states that the interest in customer-brand relationships stems from the link between these relationships and the idea of customer equity and customer lifetime value. Where the customer is seen as an asset to the firm and this is the main driver for the industry shift towards CRM (Rust, Zeithaml and Lemon 2000).

#### *2.1.2.1 Non-profit – donor relationship*

Shifting the focus to the relationship between NPOs and donors, where previously a lot of focus has been put towards emphasizing the value of relationships in fundraising without simply focusing on the cultivation of major gift donors (Waters, 2011). In order to achieve a higher donor (customer) lifetime value of each donor, the key is retention rather than recruitment. Donor retention involves focusing on existing customers with a view to develop long-term relationships, which will lead to the generation of further business. Sargeant (2001b.) state that in a large-scale analysis of database records, it was identified that even small improvements in the level of attrition can generate significantly larger improvements in the lifetime value of the fundraising database. It was found that a 10% improvement in attrition can yield up to a 200% increase in projected value, as significantly more donors upgrade their giving, give in multiple ways, recommend others to donate and ultimately perhaps, pledge a planned gift to the organisation (Sargeant 2001b). Therefore, the motivation of looking at donor retention through the lens of customer lifetime value highlights the importance of supporting the customers who are not immediately profitable. By enduring the period of low donations but knowing that a large amount of those customers, if treated correctly, will continue to become larger donors in the future. Hereafter the goal becomes to building a model to find the low-level donors who are more likely to stay and steadily increasing their donations as they progress through life (Harrison and Ansell, 2002).

Worth (2002) believe that by dedicating more time to donor retention and stewardship, the donor's loyalty to the organisation can be strengthened. This is reinforced by Rosso (1991), who states that organisations should be prepared to dedicate time and resources to develop relationships with their donors and thus ensuring a lasting relationship. In the traditional setting, an individual makes a small gift to an organisation as a result of an initial interaction and over time the fundraisers work to prove that the organisation is effective and responsible in managing these donations in order to grow the relationship. As the relationship grows the fundraisers can pursue larger donations (Waters, 2011). Hon and Gruning (1999), found a way of measuring these NPO-donor relations, by assessing their levels of trust, commitment, satisfaction and power in the relationship, building on the work by Dwyer, Schurr and Oh (1987). To go further into detail about the drivers the relationship between NPO and donor, Bekkers and Wiepking (2011) delve into seven different mechanism that drive charitable giving.

##### 2.1.2.1.1 Mechanisms driving charitable giving

The aim of this study is to investigate donor behaviour and the sentiments that affect it. In terms of literature this will be done by looking at the mechanisms that cause people to want to donate. The various mechanisms discussed here are derived from the literature review conducted by Bekkers and Wiepking (2011) as their study seemed the most comprehensive.

Bekkers and Wiepking (2011), begin their study with the discussion of awareness of need. This is the mechanism that is mostly outside the control of donors. Therefore, it comes before any conscious decision is made regarding the cost and the benefits of donating. The creation of this awareness stems from the actions of organisations in their attempt to communicate the needs of others. This mechanism is often facilitated by various forms of media, and it was found that extended coverage of natural disasters has a strong positive relationship to donations being made in support of the ones in need (Simon, 1997).

The next mechanism discussed by Bekkers and Wiepking (2011), was solicitation. This mechanisms like awareness of need, also precedes conscious decision making, but refers to the deliberate act of soliciting donors to donate. However, here it is the method through which donors are solicited which determines how effective a campaign is. It has been shown that a large majority of donations occur as a response to a solicitation and a study by Bryant, Slaughter, Kang and Tax (2003), found that 85% of donations occurred because of a request for a donation. Therefore, by actively enquiring for donations rather than passively presenting an opportunity to give, increases the likelihood that people will help (Lindskold, Forte, Haake, and Schmidt, 1997). Consequently, organisation should put more emphasis on actively soliciting as it offers the donors more opportunities to donate, and therefore people are more likely to give. However, if organisations thoughtlessly increase the number of customers contacted, it has been found that there is average decrease in donations due to donors becoming overburdened (Lesley and Ramey, 1988). To avoid donor fatigue, caused by this overburdening, organisations need to adjust their search for donors by targeting the donors who are more likely to donate, and by doing this they are increasing the marginal utility of the number of people recruited (Piersma and Jonker, 2004).

The mechanisms discussed was cost and benefit, which covers the material costs and the benefits that come with making donations (Bekkers & Wiepking, 2011). It was found by Desmet (1999) that asking for a higher donation on average in a direct mail campaign among irregular donors had a positive effect, however there was a negative effect when asking the same of regular donors. When it comes to benefits that donors gain from donating, there is not always an immediate benefit, as donors will always be better off not donating. Though, as donations are slightly motivated by material self-gain, there is a slight material benefit to oneself when donating, but the bigger benefits go to the individuals receiving the donation, which are known by the donor. Also, if contributions are made in a public space, the donors will be recognised by their fellow community members (Bekkers & Wiepking, 2011).

One of the more obvious reasons people donate money to charities is because they care about the organisation's output or the effect of the donation on the beneficiaries. In other words, altruism. Though this altruism tends to be diminished by the crowding out effect which occurs when the donors is made aware of others increasing their donation, and as a result the donor decides to reduce their donation (Bekkers & Wiepking, 2011). This is also seen when governments increase their donations on average, then other donors would decrease their average donation amount. However, evidence of the contrary does also exist showing that when government donations were increased the number of people donating increased as well, but the overall amount donated by the individual donors was minimised (Brooks, 2003).

The mechanisms of reputation refer to the societal consequences of donations, and whether people in the community reward donors for giving or punishing them for not giving donation (Bekkers & Wiepking, 2011). Most commonly giving is regarded as something positive, and thus individuals who donate to charity are often seen in a positive light, and hence receive acknowledgment and support from others (Bekkers & Wiepking, 2011). When donations occur in public, and announcements are made, verbally and non-verbally, making the donations directly observable. Then not giving to charity can have the opposite effect and damage one's reputation. As people generally prefer to give donations in a public space, making the contribution known to one's community, organisations have catered for this by selling ribbons, flower pins and wristbands to donors feeding into the practice of conspicuous compassion (Bekkers & Wiepking, 2011). Conspicuous compassion is the term for the deliberate use of charitable donations of money in order to enhance the social prestige of the donor, with a display of superior socio-economics status (West 2004). The work of NPOs in the eyes of donors, make the world a better place and the attitudes and values endorsed by donors make charitable giving attractive to donors. When the beliefs and values of an individual is aligned with the choices of an organisation there is an increase in the probability that a donation is made. Thus, philanthropy is used to reach a desired that is closer to one's view of the 'ideal' world, and it is this ideal that that depends on one's value system (Bekkers & Wiepking, 2011).

The last mechanism efficacy refers to the perception of the donors that their contribution makes a difference to the cause they are supporting (Bekkers & Wiepking, 2011). Hence a lot of people are put off donating if their chosen organisation is using expensive fundraising methods, and while it might be believed that attractive designs for the fundraising materials is often believed to be more attractive to potential donors, studies have shown quite the opposite. In a study by Bekkers and Crutzen (2007), it was found that a plain envelope raised more money than an envelope including a picture of the beneficiaries.

The sentiments of this study are Contribution, Gift/Collection and Emergency aid. Contribution mailings contains a message of asking for donors for a yearly donation, whereas Gift mailing asks the donors for an additional donation, and emergency aid mailings ask donors to donate to a specific cause. It is believed by the author that the contribution mailings should appeal to solicitation, as the NPO is encouraging donors to become continuous donors, thus asking for their loyalty. It is believed that Gift appeals to donors due to the NPO having attitudes and values, which are endorsed by the donors but also it is believed that altruism drives donors to give gifts, because they care about the output of the organisation. Emergency aid is more straight forward, and applies to the awareness of need, and the NPO appealing to the donors in a manner which enhances this need.

### 2.1.3 Relationship Marketing Activities

Another driver of the shifts in the state of a customer-brand relationship are external factors, such as marketing stimuli. Marketing stimuli are put forth with the objective of modifying the relationship between the customer and the brand, and these stimuli hopefully have a positive enduring impact on the customer's buying behaviour. Morgan and Hunt (1994) defined relationship marketing as all the marketing activities directed towards establishing, developing, and maintaining successful interactions. By understanding what influences different customer relationships, one can understand the drivers of marketing tactics. When the feelings of the customer are understood, marketing managers can use them as tools to influence the relationship marketing investments. In the current retail environment, the brands have the advantage of knowing how to position themselves and to utilise these relationship marketing tactics (De Wulf, Odekerken-Schöder, and Iacobucci, 2001).

One of the key concepts of relationship marketing is the ability of the marketers to tailor marketing offerings for everyone in order to enhance the relationship. Target marketing is the most effective tactic for building customer loyalty (Bolton, Kannan and Bramlett 2000; Sheth and Parvatiyar 1995). Using data collection and statistical methods, marketers are now able to track the transactions of their customers over time and target the marketing mix activities more effectively. As seen from De Wulf et al. (2001), relationship marketing tactics can be allocated into three levels based on Berry (1995), where the first level is tangible rewards and the second level is direct mail, and the third level is interpersonal communication and preferential treatment. In the current research the focus will be on the second level, direct mail.

Direct mail is the perceptions of the customer when it comes to the retailers' regular direct mail for information (De Wulf et al., 2001; Morgan and Hunt, 1994). Direct mail is used to keep customers informed and as a communication tool to target specific customer groups. Personalised direct mail can be used to offer immediate rewards, create interest in a new product and appeal to customer's specific needs that provide concrete benefits to customers. According to the studies by

Gouldner (1960), and his social exchange theory of the norm of reciprocity, customers should be motivated by an obligation to reciprocate because of the benefits provided by retailers (Cropanzano & Mitchell, 2005). Huang (2015), found in their study that the communication between customers and sellers is increased as the understanding of each partner is enhanced and thus increasing the closeness and trust. Further it was found that when personalisation was applied to the direct mail, the relationship quality of the customers could be enhanced (De Wulf et al., 2001).

#### *2.1.3.1 NPO Marketing Activities*

As NPOs are becoming increasingly confronted with market pressures that are typical of a for-profit organisation, such as increased competition over funding and the need to fulfil an organisational mission, they have started adopting business-like techniques (Goerke, 2003). The marketing concept, of understanding the customer has been recognised as especially important to NPOs, however it is prevalent that this concept is not fully embraced. Instead of beginning the marketing process with the donor and investigating their needs and wants, Dolnicar and Lazarevski (2009) found that NPOs have an organisation-centred mind set instead which cause a false belief that the product or service delivered is needed by the market. The customers who are the most interested in supporting the NPOs mission can be identified through careful segmentation. It is through this segmentation, that an image can be built that is attractive to those identified segments, and communication messages can be developed to suit the needs of the donors. Though there is a significant difference between for-profit organisations and NPOs, utilising a customer-centred market orientation can significantly increase the effectiveness of NPOs achieving their mission (Dolnicar and Lazarevski, 2009). NPOs need to recognise that what they are selling is not a perfect service and efforts need to be made to understand which service the market really requires.

### 2.1.4 Recency, Frequency and Monetary Model

When analysing targeted marketing activities, the objective is often estimating the likelihood of response to the marketing activity where the most commonly used approach to target marketing activities is the Recency, Frequency, and Monetary (RFM) model. The RFM analysis has been popular within direct marketing for decades (Baier et al., 2002), and the analytical technique came from the informal recognition that these three variables seemed particularly related to the likelihood that the current customers of the firm would respond to specific offers (McCarty and

Hastak, 2007).The RFM model is used to represent customer behaviour characteristics, and was developed to target marketing programs at specific customers with an objective to improve response rates (Chen, et al.,2009). For this study, recency is the number of days since the last donation, frequency is the number of donations over a set period, and monetary value is the total amount donated by a particular donor. The RFM model works on the premise that past and current purchases of customers can be used as predictors of future consumer trading patterns (Sohrabi & Khanlari, 2007). RFM analysis is utilised in a multitude of ways, and thus the analysis can mean different things to different people. Chen et al., (2001) incorporated the RFM concept, when developing an algorithm for generating RFM sequential patterns from customers' purchasing data. Arthur Hughes (2000), who advocated the procedure, applied it when sending mailings to customers, already in their database with the goal of finding the customers who are the most likely to respond to the specific mailings.

Another method of RFM is known as hard coding, explored as a comparison to the Hughes method was done by McCarty and Hastak (2007). In this method of RFM, the authors assigned a weight to each of the variables, and then created a weighted score to each customer. When assigning weights to the variables, it is generally a function of the judgement of the database marketeters, and hence it can be referred to as judgement based RFM. Another method, like hard coding, is RFM scoring as used by Miglautsch (2000), who states that there are two scoring methods, which are used to avoid the bracket creep problem. The first one is customer quintile scoring, where one sort customers in descending order and then the customers are broken into five equal quintiles. An issue however with this scoring method is in the area of frequency, as many customers have only made one purchase. For example, if the percentage of customers who have only made one purchase is 60 percent or above, then three of the five quintiles would have identical behaviour. Thus, the result is customers at the top with vastly different behaviour, and customers at the bottom with identical behaviour (Miglautsch, 2000). The second method discussed by Miglautsch (2000), is behaviour quintile scoring, which was developed by John Wirth PhD. Here instead of creating arbitrary cut-off points at certain percentage of customers, it generates cut-offs based on percentage behaviour. Five groups are still created, but the monetary score of the customers create the equal amounts of sales in each quintile. However, the same problem when it comes to frequency is still evident. Highlighted by Safari et al., (2016) one of the main objections to these scoring methods, discussed by Miglautsch (2000) and Hughes (2000), is that the weights of each of the factors is determined subjectively and based on prior knowledge about the business. Liu and Shih (2005), applied an analytic hierarchy process (AHP) to determine the relative weights of RFM variables. However, using conventional AHP has the drawback of not considering the uncertainty of human judgement. Therefore, to solve this issue Safari et al., (2016) used a fuzzy AHP and thus considering the ambiguity of the variables.

RFM analysis is a very popular approach in database marketing, due to its simplicity and reasonable performance. As seen by McCarty and Hastak (2007), the relationship between the response and the RFM variables is not assumed to be monotonic or known in advance. But at the same time, there are several disadvantages do exist. Coussement et al., (2014) found that the discretization procedure introduces a loss of explanatory information and that the customer coding procedure is arbitrary. They also found that depending on the case, there might be a need for more or less categories, such as depending on the budget finer or cruder RFM coding schemes can be employed. Further, it was found that the technique is not suited to add other features that might relate to a customer's future response behaviour (Blattenberg, et al., 2008). Another criticism made by Romero et al., (2013) is that the underlying assumptions of stochastic RFM models may not hold or they are too strict in some business settings. Thus, as relatively simple managerial heuristics lead to similar predictions in several business settings. Particularly it was highlighted that the models assume that, firstly the purchase behaviour of customers can be described by two statistics, purchase frequency and average monetary value of these transactions. Two, that customers keep the same purchase behaviour pattern over time. Three, purchase frequency and monetary value are independent, and four, customers are active during a limited period after which they permanently defect (Romero, Van der Lans, & Wierenga, 2013). Nevertheless, in the comparison study conducted by McCarty and Hastak (2007) RFM segmentation was as successful as CHAID and logistic regression in capturing likely responders to the solicitation. Furthermore, the parameters of test for RFM were as reliable as the other two methods tested. Hence, the RFM is a robust procedure in its ability to segment likely respondents.

### 2.1.5 Hidden Markov model

In a hidden Markov model, the goal is to find the non-observed states of the Markov chain. HMMs have shown to be used in various applications, across most academic fields, where there is a need to develop discrete – time models, and where continuous time processes are more suitable

(Jackson, 2011). In the last decade the number of applications in marketing has grown substantially (Netzer et al., 2017). When looking at HMMs in marketing, they are often applied to model behavioural time series, such as customer choices or firm sales. The observations follow a latent Markovian process as they evolve over time, meaning that subjects' transition over a set of latent states, and given each one of the states the subject behaves in a particular manner (Netzer et al., 2017). The main objective when using an HMM is to capture the dynamics in customer behaviour over time. When analysing the type of Markovian relationship between the current behaviour of the customer and the past behaviour, it is often referred to as state dependence. Within marketing and economics state dependence refers to that when a customer is choosing between product A and B, they might have a different utility for product A, if they previously purchased product A or B (Netzer et al., 2017). This model assumes that the customer's choice in the current period is only dependent on the customer's observed choice in the previous period and not the periods before that. By adding observed variables that may affect the customer behaviour such as advertising or price as covariates in the model, the initial assumption can be relaxed (Netzer et al., 2017). HMMs in general have two main components; a stochastic state dependent distribution, given a state the observations are stochastically determined and, a state Markovian evolution, the system can transition from one state to another according to a set of transition probabilities (Netzer et al., 2017). By approaching studies focusing on individual's transaction history as a means of creating targeted marketing activities, the HMM extends the current targeting methods by incorporating the enduring effects of marketing activities.

Brangule-Vlagsma et al., (2002) used HMM, when exploring how individual value systems change dynamically across time, to identify value segments and assumed that the observed value measurements depend on some latent value segments that followed a Markov process. They found that customers switch among segments in a structured way, when comparing the results of the HMM to a classical latent class model, which assumes fixed segments over time. Montgomery et al., (2004) explored online browsing behaviour by categorising the sequence of pages or the path viewed by users. By using HMM they were able to capture the latent states of memory effects and the transitions within the HMM showcased longer-term dynamics and abrupt changes in browsing styles. Du and Kamakura (2006) used HMM to identify unobserved and sequential household life stages from observed demographic profiles and depicted life paths that represented the sequences through which households move their life stages. When looking at studies conducted in the context of CRM, Netzer et al. (2008) applied HMM in a non-contractual setting to gift-giving behaviour in a university alumni customer relationship dataset. The model used was non-homogenous and allowed for time-varying covariates in the transitions. Netzer et al., (2008) did find that the predictive ability of HMM outperformed non-dynamic models commonly used in CRM analysis, such as the latent class model and the recency-frequency model, which follow a binary logit formulation.

# 3 Methodology

## 3.1 Research Design

The research for this thesis is going to be quantitative, as it will quantify data and extrapolate results to a broader population. The author wishes to test a theory by specifying narrow hypothesis and collect data to support or refute the hypothesis, however in this study this will take the form of research questions. Further the logic of quantitative research, is more suitable as the data is collected using standardised approaches using a wide range of variables, and the researcher searches for patterns of causal relationships between the chosen variables and test the given theory by confirming or denying the precise hypothesis (Henn, Weinstein and Foard 2009). The population for such designs is usually a large sample of representative cases referred to as respondents or subjects. The analysis is going to be statistical analysis of numerical and categorical data. With the outcome to identify prevalence, averages and patterns in data to generalise a broader population (Creswell, 2008).

## 3.2 The participants

### 3.2.1 Participant size

The participants of this research will be donors of Red Cross in The Netherlands within a six-year time span, from 1 Jan 2013 to 1 Jan 2019. The total number of donors is 1,7 million, of which there are 1,4 million contracts, which were excluded from this study, who have made 13,7 million transactions. The overall transactions are 27,4 million.

### 3.2.2 Participant Characteristics

The individuals who were selected for the study, were chosen as they fit within the set criteria. They made at least one donation in the specified time period and they spent up to €50 000 (this was done to exclude the extreme outliers). As to allow for a smoother analysis, the number of donors was limited to 1000, with 174 being exposed to Contribution, 157 to Gift and 23 to Emergency Aid in the years 2017 and 2018. A consumer was a part of the Contribution model if s/he was contacted at least once in 2017 and at least once in 2018. The same went for Gift and Emergency aid. With these exclusion rules in place the final sample contained 3410 transactions. Due to the data being panel data, the focus was on the transactional level initially rather than on a donor level.

## 3.3 Variables

| Variable Name | Measure | Description |
|---|---|---|
| Customer ID | Factor | The customer id of the donors |
| Date | Date | The date which the transaction was made |
| Total | Numerical | The amount of money donated at that transaction |
| Recency | Numerical | Days since last donation |
| Frequency | Integer | Number of donations per year |
| Year | Integer | Year of donation |
| Monetary Value | Numerical | Average amount donated per year |
| Noodhulpmailing | Binary | = 1 if emergency aid direct mail was sent to donor |
| Giftmailing | Binary | = 1 if gift/collection direct mail was sent to donor |
| Contributiemailing | Binary | = 1 if contribution direct mail was sent to donor |

## 3.4 Data Analysis

Two methods will be used to track the transitions donors to an NPO are likely to make but also how they move. An RFM scoring model was used to track how the donors moved in the past and thus when looking at the results year on year, one can analyse the patterns that emerge and make generalisations as to what segments moves where. The HMM is slightly different in this case as one does not need to separate year on year but the output of the model will display where certain segments or states are likely to move based on historical data.

### 3.4.1 RFM Scoring Model

The RFM scoring model was modelled based on the RFM package in R (Hebbali, 2019). The RFM score is computed for each customer by analysing the variables of recency, frequency and monetary value. The recency score looks at the date of the most recent transaction made by a donor and a score is given between 1 and 5, by binning the values into five categories, with 1 being the donors with the least recent score. The frequency score is assigned in as similar manner as recency, with the donors with a high donation rate throughout the period will get a higher score. The monetary score is assigned based on total amount spent within the set period, where the donors with the highest amount donated are assigned to the highest scoring bin, 5. This is summarised in table 1. A fourth score is applied of total RFM score, this initially is generated by concatenating the three other scores into a single value. However, to ensure the score would be able to be used in the HMM, it was decided to sum the scores and thus each donor would have a score between 3 (1,1,1) and 15 (5,5,5). Once the donors have been given a score, they are segmented in the following manner, based on the information at hand. How the scoring and segment creation works is that, once each donor has been given a score and they have been binned into the different segments, the program takes the segments which has too few members for any meaningful analysis along with the donors without any RFM score and places them into the segment Others. From this, it is decided which is the ideal number of segments, which meaningful analysis can be conducted. As can be seen in table 2, for this study the number of meaningful segments equal to 7.

*Table 1 Segment Classifications*

| Segment | Description | Recency Score | Frequency Score | Monetary Score |
|---|---|---|---|---|
| Champion | Bought recently, buy often and spend the most | 4-5 | 4-5 | 4-5 |
| Loyal Customers | Spend good money. Responsive to promotions | 2-5 | 3-5 | 3-5 |
| Potential Loyalists | Recent customers, spent good amount, bought more than once | 3-5 | 1-3 | 1-3 |
| New Customers | Bought more recently, but not often | 4-5 | <=1 | <=1 |
| Promising | Recent shoppers, but haven't spent much | 3-4 | <=1 | <=1 |
| Need Attention | Above average recency, frequency & monetary values | 2-3 | 2-3 | 2-3 |
| About to Sleep | Below average recency, frequency & monetary values | 2-3 | <=2 | <=2 |
| At Risk | Spent big money, purchased often but long time ago | <=2 | 2-5 | 2-5 |
| Can’t Lose Them | Made big purchases and often, but long time ago | <= 1 | 4-5 | 4-5 |
| Hibernating | Low spenders, low frequency, purchased long time ago | 1-2 | 1-2 | 1-2 |
| Lost | Lowest recency, frequency & monetary scores | <=2 | <=2 | <=2 |

Source: Hebbali (2019)

Once the segment classifications have been decided, the segmentation was applied to each year separately. Then to find the transitions of the donors, the years 2017-2018, 2016-2017, 2015-2016 and 2014-2015 were merged in a left join by customer id, which returns all records from the left table and the matched records from the right table and, if there is not match the result is null. In other words, the 2017 table was merged with the 2018 table, with the 2017 customers being the base and those who were in the 2017 table were found in the 2018 table to create information over two years. Then by arranging a table by year one can see how the donors move throughout those two years. Table 2 is a summary of the total number of donors in each segment. As is obvious from the count, this is more than 1000 donors. This is because throughout the five years the donors can exist in different segments, thus table 2 highlight all the donors who were at one point in time in each segment. For a breakdown of each segment for 2017 and 2018 please see table 6. When looking at the difference between table 1 and table 2, 11 segments were initially attempted to be modelled, as suggested by the RFM package, and in the final study segmentation, 7 segments came out. Thus, the segments Lost, Can't lose them, Need Attention, Promising and New Customers were merged into the segment Others. This was done as either there were no donors in a segment or there were too few for a meaningful analysis. The segment Others did not exist in table 1, as it appeared after running the script, as a precaution of flaws in the data, to ensure no donors fell out of the data. Further as can be seen, the At Risk segment is very small in this sample, and certain actions were taken to adjust for this when running the HMM to create more even numbered bins.

*Table 2 Full Segment breakdown*

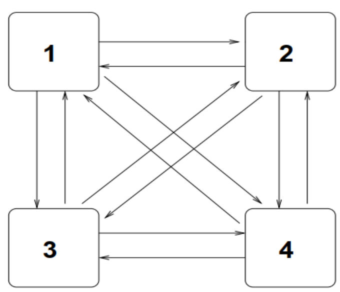
| Segment | Count |
|---|---|
| Others | 575 |
| Potential Loyalist | 473 |
| Champions | 271 |
| Hibernating | 256 |
| About to Sleep | 205 |
| Loyal Customers | 164 |
| At Risk | 17 |

When looking at the direct mailing campaigns, the information was concatenated on a similar basis where the number of contacts per donors was summed on a yearly basis. To allow for easier manipulation, the data was adjusted to look at each direct mailing campaign as a binary variable rather than looking at the number of times per year each donor was contacted through certain campaigns. Then merging the transactional data with the campaign data, was done by customer id, and ensuring that the donor was contacted in both years through the chosen campaign. One can start looking at the effects of each campaign on the donors. It was decided to focus this analysis only on the years 2017 and 2018 as the most recent data was found to be more interesting with the spike in donors in 2017 (as will be discussed in the results section).

### 3.4.2 Hidden Markov Model

The package used for running the HMM was the MSM package in R (Jackson, 2011). The msm package provides a framework for fitting continuous-time hidden Markov models with general, continuous outcomes. The model for the transitions between underlying states is specified by supplying a qmatrix, which specified which transitions are allowed and in our case all transitions are allowed, please see figure 2.

*Figure 1 General Multi-state model*

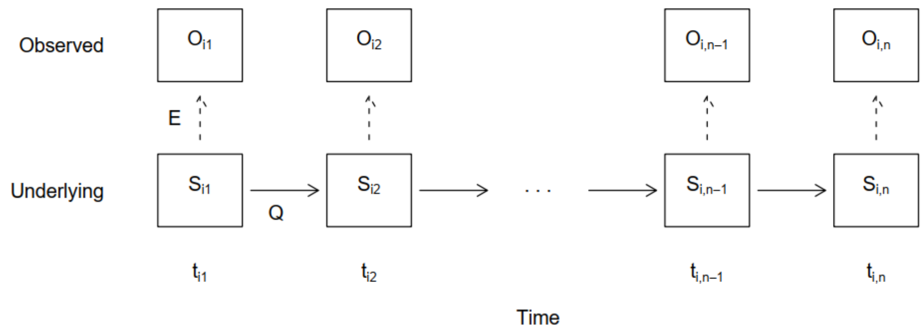



$$Q = \begin{pmatrix} q_{11} & q_{12} & q_{13} & q_{14} \\ q_{21} & q_{22} & q_{23} & q_{24} \\ q_{31} & q_{32} & q_{33} & q_{34} \\ q_{41} & q_{42} & q_{43} & q_{44} \end{pmatrix}$$

Source: Jackson (2011).

The evolution of the underlying Markov chain is governed by the specified transition intensities, as can be seen in figure 2. HMMs are mixture models, where unknown distributions are generating observations, where these distributions change over time according to states of a hidden Markov chain, as can be seen in figure 3 (Jackson, 2011).

*Figure 2 A hidden Markov Model in continuous time*




Source: Jackson (2011).

When calculating the likelihood for general hidden Markov models, it is common to use the expectation-maximisation algorithms Baum – Welch or forward – backward, but the msm package uses a direct method of calculating likelihoods based on matrix products in discrete or continuous time (Jackson, 2011). As described in the manual to the msm package the donor's contribution to the likelihood is:

$$L_i = \Pr\left(y_{i1}, \dots, y_{in_i}\right)$$

$$= \sum \Pr\left(\ y_{i1}, \dots, y_{in_i} \middle|\ S_{i1}, \dots, S_{in_i}\right) \Pr(S_{i1}, \dots, S_{in_i})$$

where the all the possible paths of hidden states,$S_{i1}, \dots, S_{in_1}$ are summed (Jackson, 2011). Further it is assumed that the observed states, the summed RFM scores per donor, $y_{i1}, \dots, y_{in_i}$ are conditionally independent given the value of the latent states, meaning that they are not influenced by the final states. Further it should be assumed that the Markov property, $\Pr\left(S_{ij} \middle|\ S_{i,j-1}, \dots, S_{i1}\right) = \Pr(S_{ij} |\ S_{i,j-1})$ applies (Jackson, 2011). The contribution of $L_i$ can now be written as a product of matrices, by separating the overall sum in the previous equation into sums over each hidden state (Jackson, 2011). The sums are gathered over the hidden initial state, the hidden second state, and so on until the hidden final state:

$$L_i = \sum_{S_{i1}} \Pr(y_{i1}\ |S_{i1}) \Pr(S_{i1}) \sum_{S_{i2}} \Pr(y_{i2}\ |S_{i2}) \Pr(S_{i2}|S_{i1}) \sum_{S_{i3}} \Pr(y_{i3}\ |S_{i3}) \Pr(S_{i3}|S_{i2})$$

$$\dots \sum_{S_{in_i}} \Pr(y_{in_1}\ |S_{in_i}) \Pr\left(S_{in_1} \middle| S_{in_{i-1}}\right)$$

where $\Pr\left(y_{ij}\middle| S_{ji}\right)$ is the emission probability density (Jackson, 2011). For general hidden Markov models, the probability density is $f_{S_{ij}}\left(y_{ij}\middle|\theta_{S_{ij}}, \gamma_{S_{ij}}\right)$. $\Pr\left(S_{i,j+1}\middle| S_{ij}\right)$ where $(S_{ij}, S_{i,j+1})$ is the entry of the Markov chain transition matrix P(t) evaluated at $t = t_{i,j+1} - t_{ij}$ (Jackson, 2011). Letting $f$ be the vector with $r$ element, or sub setting r from f, the product of the initial state occupation probability is $\Pr(S_{i1} = r)$ and $\Pr(y_{i1}|r)$, and then letting 1 be a column vector consisting of ones (Jackson, 2011). Where $T_{ij}$ is the R x R matrix for $j = 2, \dots, n_i$ where R is the number of states with $(r, s)$ entry

$$\Pr\left(y_{ij}\middle|s\right) p_{rs}(t_{ij} - t_{i,j-1})$$

Then donor $i$'s likelihood contribution is

$$L_i = fT_{i2T_{i3}}, \dots, T_{in_1}1$$

The final equation looks like this as in the research at hand there is no death state and thus there is no need to create an absorbing state.

The data used to model the HMM, was the same as the one used when modelling the RFM scores. However, as in HMM the states are not observed it was decided to use the RFM score created and use this to model a discrete staged process, in four states. The outcome distribution for all four states were Normal $(\mu_i, \sigma_i^2)$. In the hmodel argument of the msm listed the objects returned by hmmNorm constructor function. The initial values were specified for the parameters as the arguments to the constructor function. With the initial values of $\mu_1 = 8.3, \sigma_1 = 3, \mu_2 = 12.5, \sigma_2 = 1$, $\mu_3 = 4, \sigma_3 = 1$ and $\mu_4 = 14.5, \sigma_4 = 1$. These states were based on the states created during the RFM scoring but it was decided to merge the 'At Risk' state with the 'Other' state, due to the small number of donors within this state, 17. The RFM states of 'About to Sleep' and 'Hibernating' have a very similar final RFM score and thus these two states were merged into one state, and the same went for 'Champions' and 'Loyal Customers'. Therefore, the states were more similar in size. Due to the discrete nature of donor behaviour, the exact RFM state at each observation time is difficult to determine. It is made more difficult to determine when considering the high short-term variability due to the different mailing campaigns received by the donors. Therefore, an HMM based on RFM scores was used to model the natural history of donor behaviour. The same that was true for table 2 is still true for table 3 where the count is higher than 1000, the sample population, as it shows the number of donors throughout the specified time which have been present in each segment. Thus one donor could have gone through the four years been present in all four states, however this is not very likely.

*Table 3 HMM proposed segments*

| | RFM Segment | HMM State | State | Count |
|---|---|---|---|---|
| 1 | Others | Others | 1 | 592 |
| 2 | Potential Loyalist | Potential Loyalist | 2 | 473 |
| 3 | Champions + Loyal Customers | Loyal Customers | 4 | 435 |
| 4 | Hibernating + About To Sleep | Hibernating | 3 | 461 |

The specification of 0.1 as the initial probabilities for the transition matrix was decided to allow each transition to be as likely as the next. Where the dependent variable used was the RFM score created during the RFM scoring section, the time measure used was in years and, the subject identification came from Customer ID. The direct mailing campaigns were added as parameters specifying the effect of each campaign to be equal across each state. For a more technical explanation please see appendix 5.

# 4 Results

## 4.1 Data exploration

As a way of ensuring that the results from both the initial RFM scoring and the HMM models can be on some level comparable, the same data set was used. Below is an initial look at the data, before it was run through the RFM scoring script. The data used was transactional data, only the variables of Date, when the transaction was made and Total, the total amount spent on that transaction. YOrder (Year of Order) was the variable created, to help with summarising the transactions on a year on year basis.

*Table 4 Sample of initial data*

| Customer_id | Date | Total | YOrder |
|---|---|---|---|
| CN00241406 | 2014-10-08 | 25.00 | 2014 |
| CN00241406 | 2013-04-16 | 25.00 | 2013 |
| CN00241406 | 2016-09-08 | 50.00 | 2016 |
| CN00241406 | 2017-10-03 | 50.00 | 2017 |
| CN00241406 | 2018-10-30 | 25.00 | 2018 |
| CN00270028 | 2013-01-18 | 25.00 | 2013 |
| CN00270028 | 2014-01-20 | 25.00 | 2014 |
| CN00278713 | 2017-09-11 | 200.00 | 2017 |
| CN00278713 | 2016-10-17 | 150.00 | 2016 |
| CN00278713 | 2015-11-02 | 200.00 | 2015 |

*Table 5 Summary of initial data*

| Customer_id | | Date | | Total | | YOrder | |
|---|---|---|---|---|---|---|---|
| CN02880590 | 77 | Min. | 2013-01-02 | Min. | -6000.00 | Min. | 2013 |
| CN01885319 | 74 | 1st Qu. | 2014-09-15 | 1st Qu. | 10.00 | 1st Qu. | 2014 |
| CN01116143 | 49 | Median | 2016-03-07 | Median | 20.00 | Median | 2016 |
| CN00914233 | 30 | Mean | 2016-02-11 | Mean | 35.94 | Mean | 2016 |
| CN00642038 | 26 | 3rd Qu. | 2017-09-13 | 3rd Qu. | 30.00 | 3rd Qu. | 2017 |
| CN00796676 | 24 | Max | 2018-12-31 | Max | 6000.00 | Max | 2018 |
| (Other) | 3130 | | | | | | |

The summary of the initial data in table 5 showcases a variety of different customer ID's that when added together creates a sample of 3410 transactions. These transactions span from the first quarter of 2013 till the end of the fourth quarter of 2018. As no real summary can be made of the customer ids a sample of six customers are shown to highlight the number of transactions per Customer id throughout the data, and (Other) simply means the transactions not shown in this table. The total sum of transactions of customer ids not listed in the summary table are 3130. From the variable Total there are a few outliers, and consequently these outliers drive up the mean, and therefore this metric becomes irrelevant to measure when looking at the central tendency of the dataset. Hence the median becomes a better measure to understand the distribution parameters. Upon discussions with the Red Cross, there were occurrences were some donors accidentally donated too much or regretted their donation, hence there were negative numbers in the dataset. However, this was not an issue as the average/total was looked at rather than simply the maximum amount donated. To get a better idea of the breakdown of the segments and their behaviour rather than simply looking at the description in the Methodology. In figures 4, 6 and 7 the median recency, frequency and monetary value is highlighted. Further when running the linear regression analysis and the HMM, the data was broken down into a training and a test set to validate the data and it was split on an 80 to 20 percent basis. As the results show more information, it was decided to disclose the training results in the body of the thesis, but the test set results can be seen in the appendices, appendix 4 and 6.

## 4.2 Recency, Frequency and Monetary Model

Upon completing the transactional data, through the binning of customers and application of the RFM scores, one can now dive into the outcome, but please refer to table 2 for full segment summary. When looking at figures 4, 6 and 7 the behaviour of each segments regarding recency, frequency and monetary value is highlighted. From Figure 4, Hibernating and At Risk have the highest recency and thus will have a lower overall recency score. Where Champions will have the highest recency score. The segment Others contains the segments New Customers, Promising, Need Attention, Can't Lose Them and Lost. Others seem to have an overall low recency from the years 2013 to 2018. The reason for the low recency is probably due to the spike in New Customers from 2017. As can be seen in the figure below.

*Figure 3 Median Recency by Segment*

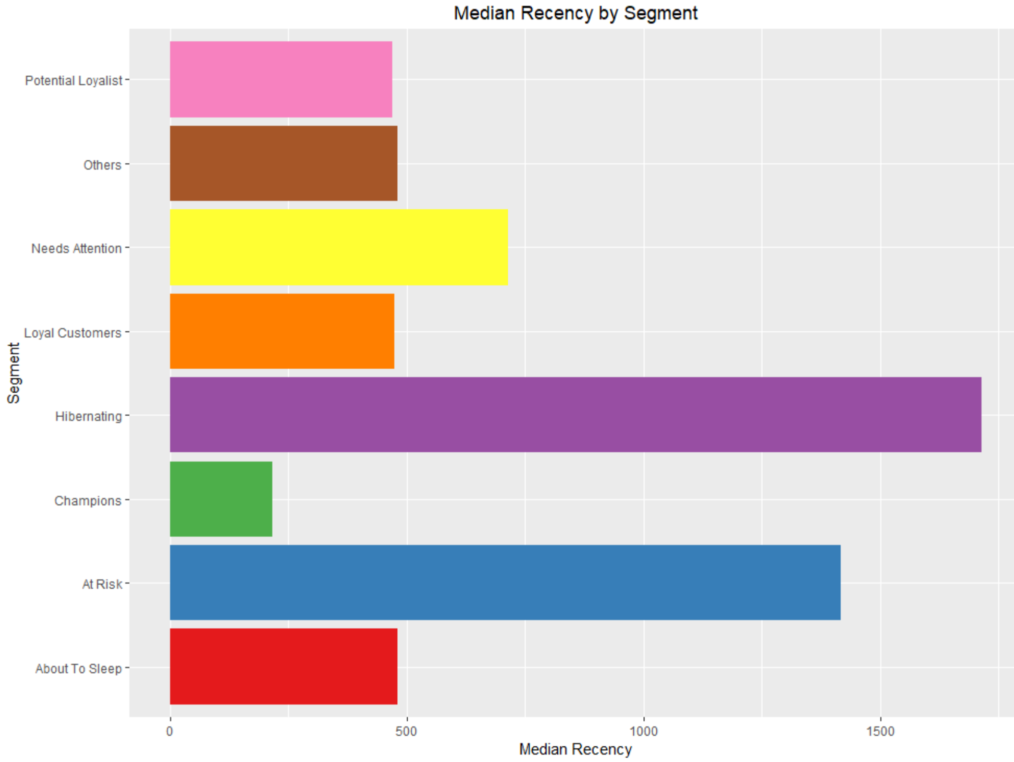
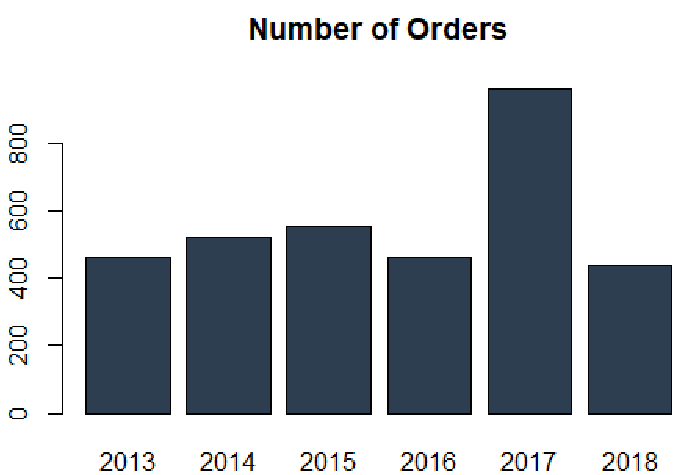



*Figure 4 Number of Orders per Year*

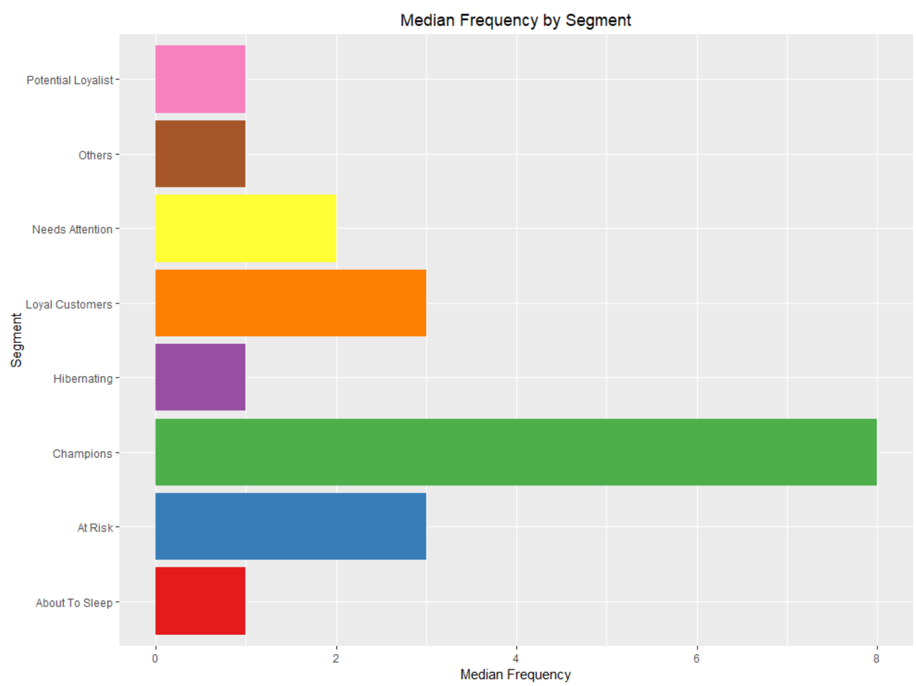


The reason for this spike, according to the Red Cross, was due to hurricane Irma which hit the island of Sint Maarten in the Dutch Antilles. Meaning that in the year of 2017 there were more customers as compared to previous and future years, as can be seen in table 6.

*Table 6 Summary of the number of donors within each segment per year*

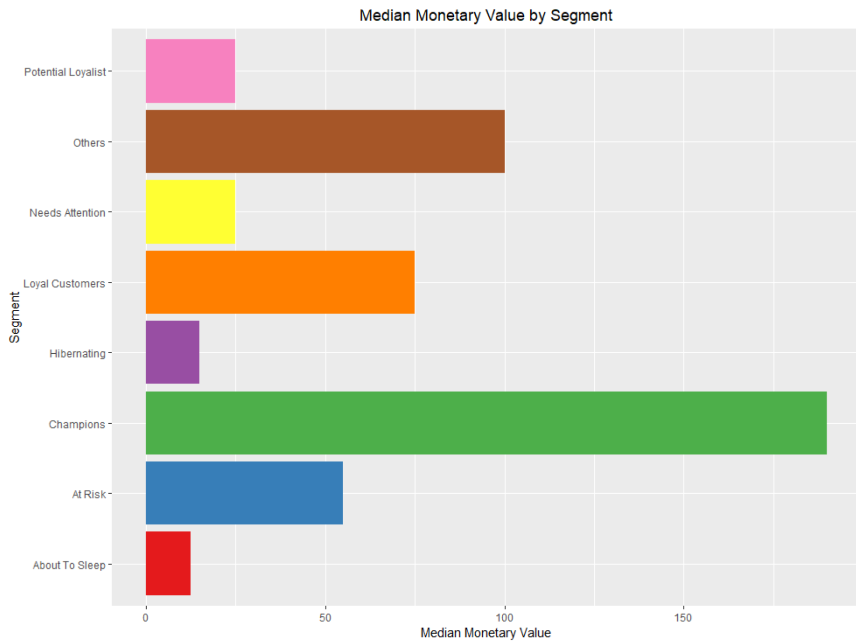
| 2017 | | | 2018 | | |
|---|---|---|---|---|---|
| | Segment | Count | | Segment | Count |
| 1 | Potential Loyalist | 240 | 1 | Others | 96 |
| 2 | Others | 225 | 2 | Potential Loyalist | 56 |
| 3 | Hibernating | 93 | 3 | Champions | 44 |
| 4 | Champions | 58 | 4 | Hibernating | 30 |
| 5 | Loyal Customers | 53 | 5 | About To Sleep | 26 |
| 6 | About to Sleep | 39 | 6 | Loyal Customers | 21 |
| 7 | At Risk | 15 | 7 | At Risk | 1 |

*Figure 5 Median Frequency by Segment*



When looking at figure 5, median frequency by segment, Loyal Customers and At Risk have the same frequency, showcasing that a higher emphasis is put on monetary value and recency, which can also be seen in the previous recency figure. For potential Loyalists the criteria for frequency was that they purchased more than once, and it seems that for this segment it must have meant that the ones who donated just once where included, as the median value is one. But overall, donors made between 1 and 2 donations between those years.

*Figure 6 Median Monetary Value by Segment*




Looking at the segment Others in figure 6, provides further evidence for the type of customers who are within it. The median value for Other is the second highest with a median value of around €100, suiting the segment of Can't Lose Them. Though, the categorisation of Can't Lose Them does not apply in terms of frequency as the frequency is so low and for the segment Can't Lose Them it should be higher. Nevertheless, the characteristics of Can't Lose Them for Other is true in terms of recency, due to the median purchase occurred just below 500 days from 1$^{st}$ January 2019. The median value for recency shows that they donated in the last year and a half, but frequency tells us that they only made one donation and monetary value tells us that they donated quite a large sum. Hence these donors seem to be a combination between Needs attention and Can't lose them.

*Table 7 Transitions of all segments from 2017 to 2018*

| Current state | Next state | Transition probability in the model: | | |
|---|---|---|---|---|
| | | Basic | Contribution | Gift |
| About to Sleep | About to Sleep | 0.000 | N/A | N/A |
| | At Risk | 0.000 | N/A | N/A |
| | Champions | 0.000 | N/A | N/A |
| | Hibernating | 0.000 | N/A | N/A |
| | Loyal Customers | 0.000 | N/A | N/A |
| | Others | 0.000 | N/A | N/A |
| | Potential Loyalist | 1.000 | N/A | N/A |
| At Risk | About to Sleep | 0.100 | 0.111 | 0.111 |
| | At Risk | 0.000 | 0.000 | 0.000 |
| | Champions | 0.200 | 0.222 | 0.222 |
| | Hibernating | 0.100 | 0.111 | 0.111 |
| | Loyal Customers | 0.100 | 0.000 | 0.000 |
| | Others | 0.400 | 0.444 | 0.444 |
| | Potential Loyalist | 0.100 | 0.111 | 0.111 |
| Champions | About to Sleep | 0.054 | 0.031 | 0.065 |
| | At Risk | 0.000 | 0.000 | 0.000 |
| | Champions | 0.541 | 0.531 | 0.484 |
| | Hibernating | 0.027 | 0.031 | 0.032 |
| | Loyal Customers | 0.135 | 0.156 | 0.161 |
| | Others | 0.108 | 0.094 | 0.097 |
| | Potential Loyalist | 0.135 | 0.156 | 0.161 |
| Hibernating | About to Sleep | 0.210 | 0.220 | 0.241 |
| | At Risk | 0.000 | 0.000 | 0.000 |
| | Champions | 0.048 | 0.051 | 0.037 |
| | Hibernating | 0.306 | 0.288 | 0.296 |
| | Loyal Customers | 0.065 | 0.068 | 0.056 |
| | Others | 0.258 | 0.271 | 0.278 |
| | Potential Loyalist | 0.113 | 0.102 | 0.093 |
| Loyal Customers | About to Sleep | 0.087 | 0.103 | 0.114 |
| | At Risk | 0.217 | 0.026 | 0.029 |
| | Champions | 0.217 | 0.231 | 0.229 |
| | Hibernating | 0.087 | 0.103 | 0.114 |
| | Loyal Customers | 0.152 | 0.154 | 0.143 |
| | Others | 0.326 | 0.308 | 0.286 |
| | Potential Loyalist | 0.109 | 0.077 | 0.086 |
| Others | About to Sleep | 0.044 | 0.036 | 0.045 |
| | At Risk | 0.000 | 0.000 | 0.000 |
| | Champions | 0.089 | 0.036 | 0.000 |
| | Hibernating | 0.022 | 0.036 | 0.045 |
| | Loyal Customers | 0.044 | 0.036 | 0.045 |
| | Others | 0.667 | 0.750 | 0.727 |
| | Potential Loyalist | 0.133 | 0.107 | 0.136 |
| Potential Loyalist | About to Sleep | 0.125 | 0.143 | 0.167 |

| | | | | |
|---|---|---|---|---|
| | At Risk | 0.000 | 0.000 | 0.000 |
| | Champions | 0.125 | 0.143 | 0.167 |
| | Hibernating | 0.083 | 0.143 | 0.167 |
| | Loyal Customers | 0.042 | 0.000 | 0.000 |
| | Others | 0.333 | 0.143 | 0.000 |
| | Potential Loyalist | 0.292 | 0.429 | 0.500 |
| Sample size | | 226 | 174 | 157 |

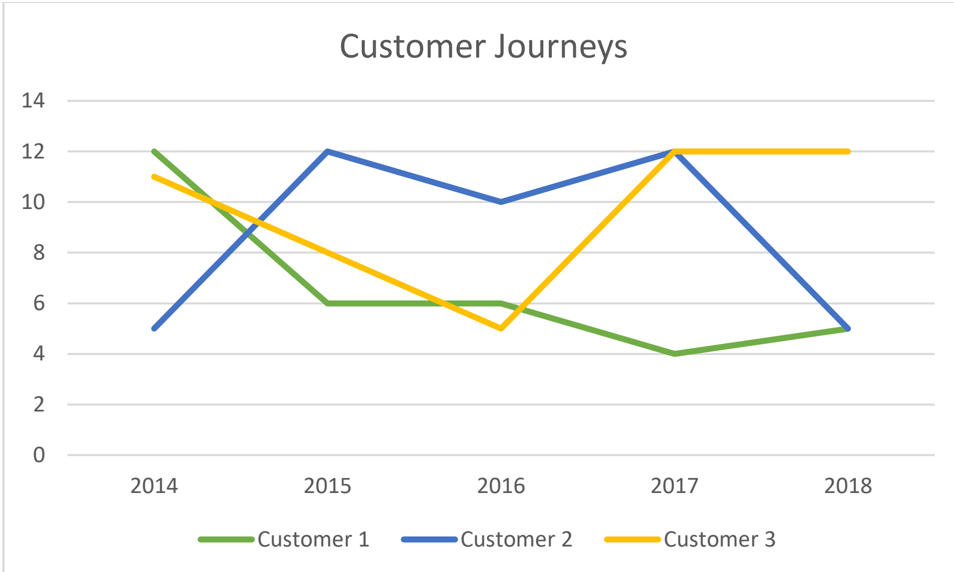
When looking at the transitions in the basic column in table 7, when no direct mail campaign was applied, it is clear that a large proportion from each segment transfer into the Others segment, with At Risk having the largest percentage of 40. The relatively small sample size does not provide sufficient information to draw definite conclusions. Interestingly, a large number of donors transferred from lower RFM scored segments into higher ones, such as Champions, Loyal Customers and Potential Loyalists. When looking at the transfers of segments from 2014 until 2018 the common that appear are that the donors in the About to Sleep segment are more likely to transfer to the lower state of hibernating rather than a higher state. For Champions, as it is the segment with the highest average RFM score, these donors can either stay put or transfer to a lower state. The most common lower state for Champions to transfer to is Loyal Customers. The same goes for Hibernating, where they are a very low state and therefore it seems to be more common for them to transfer to About to Sleep, meaning they are not very active. What was also seen was that the donors in the Hibernating state would also transfer to Others, meaning that they most likely are lost or need attention to be revived. Loyal Customers on the other hand show the theme of transferring either up one state to Champions or transferring to Others. As this state does contain both positive and negative states, one can only deduct which state they most likely transferred to. With needing attention seeming like the most promising one. For the segment Potential Loyalists; they either transfer to a higher state of Loyal Customers or to a lower state of Hibernating.

The Contribution column in table 7 shows the results when running the model with a focus on only the donors who received a direct mail regarding Contribution in both 2017 and 2018. Here it can be seen that there is a large percentage moving into About to sleep from At Risk, Hibernating, Loyal Customers and Potential Loyalists. Additionally, there is also a large proportion of donors who move into Hibernation while exposed to Contribution. However, there is also a larger proportion of donors moving into Champion from At Risk, Loyal Customers and Potential Loyalists. This also goes for At Risk and Potential Loyalists increasing their RFM score and thus moving into Loyal Customers. Thus, there seems to be an effect where the donors who are already quite loyal move into even more loyal states, but donors who are not so loyal move into even less loyal states.

When looking into the effects of Gift, which focuses on the donors who received direct mail regarding giving a Gift to the Red Cross in 2017 and 2018, as compared to the basic model, the same pattern as was seen in Contribution is apparent here as well with a large proportion of donors moving into the About to Sleep state.  Further, with the same transition percentages being higher for Gift compared with the basic model, as the ones being higher for Contribution when compared to the basic model, so Champions, Hibernation, Others and Potential Loyalists. However, where there were more donors transitioning from At Risk and Potential Loyalists to Loyal Customers, there were fewer when exposed to Gift. But there were more donors transitioning from Champions to Loyal Customers.

Overall, when looking at the basic transitions between 2014-2015, 2015-2016, and 2016-2017, please see appendix 1-3, the patterns that become clear are About to Sleep transitioning into Hibernation, Champions transitioning into Loyal Customers,  Loyal Customers transitioning into Champions, Potential Loyalists transitioning into either Loyal Customers or Hibernating and Hibernating into About to Sleep. Therefore, the lower scoring segments are more likely to go even further down, and the higher segments seem more likely to transition into higher segments. In figure 7, the author has highlighted the customer journey of three customers. As can be seen, each individual behaves very differently from one another, and it seems like the year which donations were made does not impact donations overall, when looking at these donors.

*Figure 7 Three Customer Journeys*




When running the linear regression to find the influence of the campaigns on the dependent variable RFM score, which is measured using the combination of the scores from the RFM scoring model. The independent variables, Contribution, Gift and Emergency Aid are binary and are measured on the basis if the donor received a direct mail regarding on of these campaigns in a year. In this study the reasoning behind who received what campaign was not dependent on the RFM, as this method is not yet applied by the Red Cross.

$$RFM\ Score = \beta_0 1 + \beta_1 Contribution + \beta_2 Gift + \beta_3 Emergency\ Aid$$

When looking at the results of RFM score as a linear regression, of the validation data set, please see both training and validation set in appendix 4, we can further see that there is a negative effect on RFM score with Contribution and Emergency Aid. When looking at the test set, there was not a negative effect coming from Emergency Aid, however this was believed to be because of the small sample contained in the test set. However, in both the training set and test set Emergency aid was not significant. Thus, the data is valid as there is no major changes to the direction of the data when looking at both the training set and the test set, the difference lies in the magnitude of the effect. The R squared of the linear regression was 0.08 and the adjusted R squared 0.079, though this may seem small, but as the intercept, Contribution and Gift were significant it does not seem like a big issue.

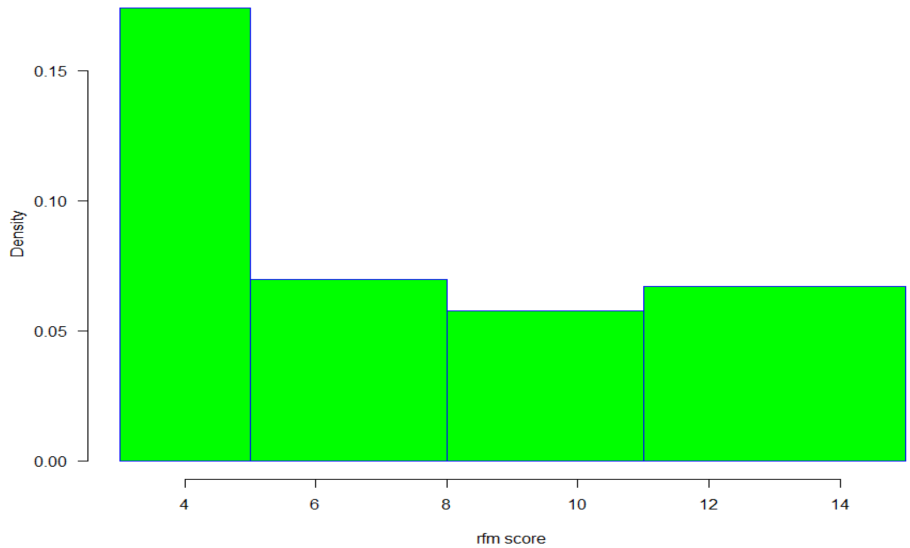
*Table 8 Linear Regression model of RFM Score*

| | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| (Intercept) | 8.409 | 0.266 | 31.584 | <2e-16 |
| Contribution | -2.343 | 0.301 | -7.774 | 1.74e-14 |
| Gift | 2.383 | 0.273 | 8.742 | < 2e-16 |
| Emergency Aid | -0.054 | 0.817 | -0.067 | 0.947 |

## 4.3 Hidden Markov Model

When running the HMM, the information that is given are the maximum likelihood estimates and the 95% confidence intervals. Before applying the effect of the different direct campaigns, the HMM was run on the yearly RFM scores, the same as the basic RFM model, based on the panel data created when modelling the RFM scores. The figure below displays a histogram of the states created in preparation for running the HMM, where a larger proportion of donors are in the state with the lowest RFM scores. However, the other three states have a relatively similar density. As discussed in the methodology, due to the strict nature of running an HMM in the R package MSM, there was a limitation to the number of states that could be used and, in the end, what worked was four states. Looking at the shape of the histogram, figure 8, it becomes clear that there is a strong correlation with this output as with the output of figure 3, figure 5 and figure 6, where a large proportion of the segments have relatively low values across frequency and monetary value, as well as high values across recency, in other terms a low RFM score.

*Figure 8 Histogram of RFM score*




In table 9, the results of the HMM model can be seen. In the basic model all donors were considered, no matter if they received any direct mail or not. Whereas, similarly to the initial RFM model, the Contribution and Gift models were run with only the donors who were contacted with these campaigns at any point within a year. Hence, the number of donors present in these two models vary between themselves. Thus, the results of the targeted donors will differ from the basic model, which did not take the campaigns into consideration. When running the HMM based on the RFM scores, four hidden states with the following maximum likelihoods were found, please see table 10. Relating back to section 3.4.2, the initial and secondary states from table 10 are the unobserved states, $S_{i1}, \dots, S_{in_1}$ in the equation and the maximum likelihood of each transition is $L_i$. The normal distribution parameters, seen below table 10, refer to the initial values which specified the parameters for the arguments to the constructor function.

*Table 9 HMM results*

| | | Maximum Likelihood | | |
|---|---|---|---|---|
| Initial State | Secondary State | Basic | Gift | Contribution |
| Others | Others | -0.750 | -0.788 | -0.766 |
| | Potential Loyalists | 0.335 | 0.059 | 0.343 |
| | Hibernating | 0.410 | 0.400 | 0.377 |
| | Loyal Customers | 0.005 | 0.329 | 0.046 |
| Potential Loyalists | Others | 0.661 | 0.046 | 0.783 |
| | Potential Loyalists | -1.539 | -0.048 | -0.886 |
| | Hibernating | 0.003 | 0.000 | 0.003 |
| | Loyal Customers | 0.875 | 0.002 | 0.099 |
| Hibernating | Others | 0.300 | 0.310 | 0.303 |
| | Potential Loyalists | 0.002 | 0.000 | 0.006 |
| | Hibernating | -0.303 | -0.313 | -0.310 |
| | Loyal Customers | 0.001 | 0.002 | 0.001 |
| Loyal Customers | Others | 0.017 | 0.693 | 0.055 |
| | Potential Loyalists | 1.250 | 0.061 | 0.006 |
| | Hibernating | 0.002 | 0.000 | 0.003 |
| | Loyal Customers | -1.268 | -0.754 | -0.065 |

Others - normal distribution
Parameters:

| | Estimate |
|---|---|
| Mean | 8.382 |
| sd | 3.247 |

Hibernating - normal distribution
Parameters:

| | Estimate |
|---|---|
| Mean | 4.206 |
| sd | 0.916 |

Potential Loyalists - normal distribution
Parameters:

| | Estimate |
|---|---|
| Mean | 12.655 |
| sd | 0.910 |

Loyal Customers - normal distribution
Parameters:

| | Estimate |
|---|---|
| Mean | 14.657 |
| sd | 0.480 |

Consequently, when applying the direct mailing campaigns, these means, as seen in table 10, were considered but also adjusted to avoid numerical overflow when running the HMM.

When Gift is applied, please see appendix 7, the likelihood of transferring from Others to Hibernating and Loyal Customers is much higher than transferring to Potential Loyalists. As we saw in the basic model, here the same is true where there is a higher likelihood of transferring to Others from Potential Loyalists, and the same is true for Hibernating and Loyal Customers. When Gift is applied to the hidden states, the means of Others and Hibernating stay within a similar range to the basic model. However, Potential Loyalists has a mean of 14 and Loyal Customers a mean of 12. More so the observations coinciding with Gifts have on average an increased RFM score of 0.4.

When applying Contribution, please see appendix 8, donors are about as likely to transfer from Others to Potential Loyalists as from Others to Hibernating, as was seen in the basic model. Further, what is prevalent is that donors are from all other states more likely to transition to Others. However, when Gift is applied, donors have a higher likelihood of transferring from Hibernating to Loyal Customers rather than Potential Loyalists as all the other models show. What distinguishes Contribution from Gift is that when contribution is applied the average RFM score decreases by 0.37. However, what can be seen from these results are that except for Others, donors seem to have a higher likelihood to transfer to a state that has a higher average RFM score, even though on average that score is lower for Contribution. For emergency aid which could not be applied to the RFM model due to the lack of year on year data, and for the HMM, the analysis ran but displayed similar results as the basic model, which could be due to the fact that it was not significant in the linear regression. Nevertheless, what can be gained from the RFM is that the lower segments are positively affected when exposed to Gift, but when the same segments are exposed to contribution, there is a negative effect. When starting from Others, which has an average RFM score of 8, it is more likely to transfer to the lowest level of Hibernating. Yet when looking at the second most likely transfer for the basic model displays a higher likelihood for a transfer to Potential Loyalists. When Gift is applied the likelihood is higher for Loyal Customers. This same pattern is seen when looking at the initial state of Hibernating, where for the basic model there is a positive increase for some of the donors, but this positive increase is enhanced further when Gift is applied. However, all segments are more likely to transfer to Others, which in terms of the RFM segments is the Others state. Though there was a high prevalence in the RFM model for transfers to this state, it was not nearly as prevalent as in the HMM. When comparing the campaign with the higher maximum likelihood, Contribution has a much higher likelihood of transfer from Others to Potential Loyalists, whereas a similar magnitude is seen when transferring from Others to Loyal Customers under Gift. Looking at transfers out of Potential Loyalists, the biggest difference in magnitude of maximum likelihood can be seen when transferring to Others and to Loyal Customers under Contribution. Transferring out of Hibernating was quite similar for both Gift and Contribution and thus no major difference is seen. As for transferring out of Loyal Customers, the biggest difference can be seen when transferring to Others and to Potential Loyalists under gift. When looking at the overall direction of transfers, table 10, Gift has a higher impact on moving donors to a higher state, whereas for Contribution it is equal.

*Table 10 Impact of Campaigns*

| Contribution | | | Gift | | |
|---|---|---|---|---|---|
| Initial State | Transfer State | Direction | Initial State | Transfer State | Direction |
| Others | Potential Loyalists | Increase | Others | Hibernating | Decrease |
| Potential Loyalists | Others | Decrease | Others | Loyal Customers | Increase |
| Potential Loyalists | Hibernating | Decrease | Hibernating | Others | Increase |
| Potential Loyalists | Loyal Customers | Increase | Hibernating | Loyal Customers | Increase |
| Hibernating | Others | Increase | Loyal Customers | Others | Decrease |
| Loyal Customers | Hibernating | Decrease | Loyal Customers | Potential Loyalists | Increase |

When looking at the training set and comparing it to the test set of the HMM, there is no real difference between the transition likelihoods between states. There is however a difference when looking at the mean and standard deviation of each state. In the test set the overall mean was slightly lower than in the training set, and the standard deviations slightly higher. The biggest difference was seen for Potential Loyalists which dropped from 12 in the training set to 10 in the test set.

*Table 11 HMM Basic Test results*

Others - normal distribution
Parameters:

| | Estimate |
|---|---|
| Mean | 7.916 |
| sd | 3.648 |

Hibernating - normal distribution
Parameters:

| | Estimate |
|---|---|
| Mean | 4.369 |
| sd | 0.959 |

Potential Loyalists - normal distribution
Parameters:

| | Estimate |
|---|---|
| Mean | 9.967 |
| sd | 1.998 |

Loyal Customers - normal distribution
Parameters:

| | Estimate |
|---|---|
| Mean | 13.565 |
| sd | 1.210 |

To allow for easier comparison to the transition probabilities of the RFM scoring model, the results of the HMMs were applied to a function which estimates the five year transition probabilities, as can be seen in table 12.

*Table 12 Transition Probabilities of HMM*

| | | Maximum Likelihood | | |
|---|---|---|---|---|
| Initial State | Secondary State | Basic | Gift | Contribution |
| Others | Others | 0.004 | 0.050 | 0.307 |
| | Potential Loyalists | 0.249 | 0.554 | 0.155 |
| | Hibernating | 0.467 | 0.328 | 0.391 |
| | Loyal Customers | 0.280 | 0.068 | 0.147 |
| Potential Loyalists | Others | 0.006 | 0.052 | 0.091 |
| | Potential Loyalists | 0.689 | 0.682 | 0.806 |
| | Hibernating | 0.083 | 0.201 | 0.069 |
| | Loyal Customers | 0.222 | 0.066 | 0.034 |
| Hibernating | Others | 0.003 | 0.043 | 0.305 |
| | Potential Loyalists | 0.034 | 0.240 | 0.087 |
| | Hibernating | 0.939 | 0.654 | 0.483 |
| | Loyal Customers | 0.024 | 0.064 | 0.125 |
| Loyal Customers | Others | 0.002 | 0.067 | 0.313 |
| | Potential Loyalists | 0.030 | 0.476 | 0.181 |
| | Hibernating | 0.022 | 0.294 | 0.339 |
| | Loyal Customers | 0.946 | 0.162 | 0.166 |

In this table we can see that the magnitude differences when looking at the maximum likelihoods of transitions out of Others are the same when looking at the transition probabilities, where Contribution has a bigger impact when transferring to Potential Loyalists and Gift has a bigger impact when transferring to Loyal Customers. As for transferring out of Potential Loyalists, here the same results are not seen. The probability of transferring out of Potential Loyalists to Others and Loyal Customers, for both Contribution and Gift the probabilities are quite similar. The difference is bigger when looking at transferring into Hibernating, with Contribution having a bigger impact. Transferring out of Hibernating to Others has a larger probability under Gift and transferring to Potential Loyalists has a larger probability for Contribution. When looking at probabilities of transferring out of Loyal Customers the biggest differences come are under Gift when moving to Others and moving to Potential Loyalists under Contribution.

## 4.4 Robustness

### 4.4.1 Increasing sample for RFM Scoring of Contribution and Gift

As discussed previously, the data was split into a training and a test set for the linear regression and for the HMM. The reason for not doing the same when running the initial RFM scoring model was because it performs much better when the data set is increased rather than made smaller. Thus, to test the robustness of the RFM as well, it was decided to re-run the same RFM script but with a data set of 203,734 transactions, please see appendix 10. When doing this, the increase in overall information was very clear, and the percentages of transitions became much more detailed. However, when comparing the original sample to this new larger sample the same transition intensities were shown.

The main differences to Contribution were that About to Sleep was added as there was now sufficient data to see transitions, so from the updated data we can see that a large proportion of donors transferred into being Potential Loyalists. When looking at At Risk before there were more donors transitioning into Others (44%), but when looking at the larger sample we can see that Other still has the highest transition percentage but now we also see donors transitioning into Loyal Customers and staying in At Risk. For Champions, previously donors either transitioned to Loyal Customers or Potential Customers whereas in the larger sample we can see that less donors stay in Champions and a larger percentage of donors' transition to Other instead of Potential. For Hibernating there is not a large difference between the smaller sample and the larger sample. For Loyal Customers here the distribution is also about the same, but with less donors transitioning into Others and more donors transitioning into Hibernating. For Others, in this segment the majority still stay within the same segment and very few transitions to any other. Finally, for Potential Customers, in the small sample there was an even break down in transitions between the different segments, but in the larger sample we can see that more donors transition into Others and About to Sleep.

When looking at the impact of Gift on About to Sleep, a large proportion moves into Champions, Others and Potential. For At Risk there is more of an even distribution between the transitions rather than the majority transitioning into Others. As for Champions the largest shifts were originally to Loyal Customers and Potential Customers whereas now a much higher percentage transitions into Other. Hibernating, in the small data set the bigger shift were to About to Sleep and Others, and the same can be seen in the larger data set as well. For Loyal Customers the same transitions are seen with very little difference in terms of percentage can be seen in both data sets. Others also has a very similar distribution between the small and the large data set, and for Potential Customers, in the small data set we can see that the donors that do not stay in Potential Customers either transition to About to Sleep, Champions or Hibernating, while when looking at the large data set there is more diversity with the larger percentages are maintained to about to Sleep, Champions, Loyal Customers but with the highest number of donors transitioning into Others.

### 4.4.2 Removing Recency from Analysis

As the panel data was created on a year to year basis, it was decided to see the influence on the data when recency was removed. The reason for this decision was because certain doubts arose when discussing the impact of recency when someone who donated just once in January would have a lower recency score compared to someone who also just donated once but in December. To highlight the effect of this shift, the linear regression was run again as well as the Gift and Contribution HMM. Thus, emphasising the effects regarding the campaigns. From table 13, the biggest different when removing recency is the decrease in the intercept estimate. Other than that, it seems like there is not a very big difference between the original model and this version.

*Table 13 Linear Regression model of RFM Score with Recency removed*

| | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| (Intercept) | 4.993 | 0.173 | 28.833 | <2e-16 |
| Contribution | -1.164 | 0.197 | -5.923 | 3.99e-09 |
| Gift | 1.642 | 0.177 | 9.259 | < 2e-16 |
| Emergency Aid | -0.238 | 0.568 | -0.419 | 0.676 |

When removing recency from the HMM models, naturally the script had to be adjusted to suit the new RFM score, which now ranged from 2 to 10. When looking at the new Gift and Contribution output, please see appendix 11, the effect of the campaigns on the overall RFM score has drastically changed. Here the effect of Gift on the average RFM score is now 0.07, which is a lot lower than 0.40, as in the original model. However, the new scale does need to be kept in mind. As for Contribution, the change is a lot bigger here as in the new model, Contribution has now a positive effect on the average RFM score. With an increase of 0.14, which is even higher than the impact of Gift. The reason for this shift is unclear as in the linear regression Contribution still had a negative impact. When looking at the differences in transitions, in the original iteration, Gift had a larger impact on states Hibernating, Others and Loyal Customers, whereas in the new iteration it shows to only have a large impact on Potential Loyalists. In the initial iteration, Hibernating was the one with the lowest mean RFM score and in the new iteration it was Potential Loyalists. As for Contribution, in the initial iteration there was a larger impact on Potential Loyalists, the second to largest mean RFM score, and in the new iteration the impact had shifted towards Others, Potential Loyalists and Loyal Customers. Therefore, even though the magnitude of effect changed, it does seem like Gift is able to have a greater impact on the lower segments and that Contribution has more of an impact on the higher segments.

# 5 The Discussion

## 5.1 Research Questions

### 5.1.1 Research Question 1

*What is the difference in donating behaviour of donors when exposed to the direct mailing campaigns with sentiments related to contribution, gift/collection or emergency aid?*

From the information gathered in the literature review, it was strongly believed that Contribution would have a strong positive effect on donating behaviour. Through the analysis of the gathered data it is however clear that this hypothesis is largely untrue. There was a positive impact on donors moving from At Risk to Champions, Loyal Customers and Potential Loyalists, however the effect was not as impactful for those in segments Hibernating, and Others. However, there was a positive effect of moving Potential Loyalists and Loyal Customers into higher segments. Consequently, one cannot say the effect was that positive, as the negatives might outweigh the positives. When looking both at the probabilities presented by the RFM as well as the likelihoods presented by the HMM, they are both in agreement over that there is a negative correlation between direct mailing containing Contribution and donor behaviour. The reason for this behaviour could be because the Red Cross is sending Contribution focused direct mail campaigns to a larger customer base and perhaps donors are becoming overburdened, which is reinforced by Lesley and Ramey (1988). As mentioned by Piersma and Jonker (2004), this donor fatigue can be minimised by optimising the search for donors and figuring out what segments are more likely to respond. By doing this they should be able to increase the marginal utility of the number of people solicited. Currently the Red Cross does not use the segments that were created in this thesis, but through the adoption of these segments they should be able to target their more loyal customers more actively. But also, be able to more carefully control who receives what campaign and to avoid contact fatigue.

Looking at the Gift direct mailing campaign which is used to encourage a one off payment and are not used to increase loyalty. There was a positive correlation between the campaign and RFM score growth, with both the RFM and HMM. Perhaps this was because the campaign does not ask for loyalty but simply a single donation. Potentially because of this the donors felt that the one-off gifts did not come with a commitment and consequently, the donors were more likely to donate. As people like to feel as if their donations are unique, this might encourage them to give larger amounts or to give more often which will give them a higher RFM score. Accordingly, by appealing to these donors in such a manner, it is probably more suitable rather than also sending them contribution mailing as well.

As for Emergency Aid, the initial RFM transitions, the analysis could not be run due to there being no data from 2017. For the HMM transitions, the results were not identical to the transitions when Contribution was applied but they displayed similar patterns. When looking at the impact of each of the states of the HMM when Emergency aid was applied there was a negative effect, similar to Contribution which also had a negative effect on the overall RFM score of the segments. Nevertheless, as Emergency aid was found to be not significant, no conclusions can be drawn from the data.

### 5.1.2 Research Question 2

*To what extent will Contribution, Gift or Emergency Aid elicit a higher level of loyalty?*

When looking at the RFM output there is about an even split between the effect of Contributions and Gift, but as Emergency aid was not significant it is not included in this discussion. This even split is apparent when looking at which campaign caused a higher percentage to move from a lower segment to Potential Loyalist, Loyal Customers or Champions. From the initial state of At Risk, 22 percent moved to Champions when sent a Gift direct mail, where the same percentage, made the same transition when Contribution was applied. Starting from Hibernating, 6.8 percent moved to Loyal Customers with Contribution and 5.6 percent made the same transition under Gift. Starting from Others, under Gift, 13.6 percent moved to Potential Loyalists, whereas under Contribution 10.7 percent made the move. Under Contribution, 3.5 percent moved from Others to Champions, and zero percent made this move when influenced by Gift. Starting from Potential Loyalist, 16.7 percent made the move to Champions under Gift and 14.3 percent moved to Champions for Contribution. From Loyal Customers, 22.8 percent transitioned to Champion under Gift and for Contribution the percentage was 23. In conclusion, using Gift compared to Contribution, causes a higher percentage to move from Potential Loyalist to Champion and from Others to Potential Loyalists. Contribution on the other hand causes a higher percentage to move from Hibernating, Loyal Customers and Others to Champion. Also, Contribution cause more to move from Hibernating to Loyal Customers and to Potential Loyalist. Therefore, it does seem as if Contribution does cause more customers to move from lower levels of loyalty to higher levels of loyalty. When looking at the transitions of donors through the HMM, it does seem like

Contribution cause a higher likelihood in transfers to Potential Loyalists and Loyal Customers, especially when looking at transfers from Others to Loyal Customers, Potential Loyalists to Loyal Customers and Hibernating to Potential Loyalists. For Gift, there was a higher likelihood for transferring from Others to Potential Loyalists and Hibernating to Loyal Customers. Therefore, when looking at both analyses, there does seem to be a pattern that donors are influenced by Contribution and it does cause them to become more loyal.

## 5.2 Limitations

A significant limitation of this study was the restrictions that running the HMM analysis had on the overall sample. As the author wanted to ensure that the same size data was used for all analyses, the sample had to be very small, as compared to the size of the population available. This caused the RFM analysis to potentially not be able to capture as many segments, and hence the segment Others was quite large and contained five separate segments. This is not ideal as it caused the standard deviation for this segment in the HMM to be three rather than one as it was for the other three segments. Further, the segments contained in Others were varying in their meaning, as it contained New Customers, Promising, Need Attention, Can’t Lose Them and Lost. Where, Need Attention and Can’t Lose Them would have had a higher average RFM score and lost and new customers would have had a lower average RFM score. A limitation of the linear regression model was the direct marketing activities were assumed to be independent, however in the future donors will receive direct marketing campaigns based on their RFM scores, and so the activity variables won’t be independent anymore. Another limitation was the fact that not much information could be gathered as to the impact of Emergency Aid. This could of course be due to the underlying reason as to why people decide to donate when approached with these messages. Further, as Contribution is asking for people to become contractual donors, and it was not possible to include contractual donors in this research as they do not receive direct mailing, this shift was not captured. Hence, even if the donors did become more loyal, in terms of starting a contract, this would not have been captured. Another limitation was regarding the HMM, due to the lack of previous experience in running an HMM the author was not as competent when it came to adjust the HMM to fully suit the data. Rather than being able to choose the number of states that gave the most information, the author had to choose the number of states that the model allowed to be run. Which for this case was four. Ideally, the analysis would have benefitted from having more output to adjust the data according to. Nevertheless, as the only number of states that were possible were four, it is not actually known if this is number of states was if fact the most suitable. Further, it was found that due to the low average transaction count of the donors, there was only four bins for frequency, 1, 3, 4 and 5. Initially it was tested to see if increasing the sample would change this, however this was not the case and it was simply due to how the R package was built, along with the behaviour of the donors. For this reason, other RFM methods were attempted, however in the end it was found to be the best option as it allowed for a smoother transition from the RFM to the HMM.

## 5.3 Future Research

To resolve the issue of the small sample, leeway should be allowed to use a much larger sample for the RFM model, as the model can handle larger sample sizes. The RFM model works much better when allowed to process much more information, for the reasoning behind this please refer to section 4.4 on robustness. Also, to capture the effect of the contractual donors, in the future it would be interesting to look at the effect of the contribution mailing on the new recruits. This could be done by creating a separate segment, which states if the donor is in a contract with the Red Cross or not. Thus, the research would be able to capture which direct mail encourage donors to do start donating regularly, and hence seeing if contribution does spark this interest or if other direct mailing encourages recurring donations as well on a contractual basis. Further, it would be interesting to test the validity of the research and the flexibility of the R script created by exploring data from both other charities but also the data of other firms to see how the analysis holds up. Especially it would be interesting to try and push the HMM further and see if one can get more output options to choose from.

## 5.4 Implications for Managers

The goal of this thesis was to show the importance of segmentation, of all customers and not only the ones who donate the largest donations. Through this display how campaigns impact the various segments but also show how different methods can be used for similar returns. The aim is that the findings of this research will be useful for organisations and help them retain more of their smaller customers and allow them to build up a strong base by investing into these customers and nurturing them and thus encouraging them to become major donors in the future. This should not be done by over exposure to campaigns but through careful decision making regarding who to send what campaigns to. Then hopefully, by focusing direct marketing campaigns on the donors who are more likely to respond, organisations should be able to save on the cost of direct mail.  But also, by nurturing donors the overall recruitment costs could be lowered as less emphasis would be put on recruiting new donors. Because the focus should shift to retaining donors. Further, by creating more accurate targets for the direct mailing campaigns, donor fatigue should also be minimised as donors would not be overburdened with a plethora of direct mail. The donors could perhaps feel dejected, that even though they donate to one campaign they are still immediately contacted regarding another, showing that the organisation does not really care how or how much they are contacting their donors. By refocusing the marketing campaigns to show care for the customers, and customising the campaigns to suit the segment, which they are currently in, organisations should not only be able to reduce costs and donor fatigue, but also potentially customer churn. Though it was not tested in this thesis, one can draw the conclusion that by minimising donor fatigue, customer churn should also be minimised. Highlighting the importance of careful segmentation, and the overall impact this has on entire organisations.

## 5.5 Conclusion

When looking at the information provided by both the RFM scoring model and the HMM, both models have their own separate merits. The RFM model provides more intricate results as to showcase the transitions the analyst needs to separate the data on a time basis and thus the transitions can be tracked period on period. The RFM further used percentages of how the customers moved and does not provide predictive measures on how these segments will move in the future. However, due to the simplicity of the model one can simply run the model every year or on a month to month basis without too many restrictions in terms of code complexity. As the code will most likely not change from the first iteration, but further, the code is very easy to manipulate. The HMM model provides more interesting data in terms of predictions as it shows the maximum likelihood of a segments transferring to another segment. Thus, ideally the two should be used in union to showcase a snapshot of the past behaviour of the donors but also the likelihood of how those segments will move.

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# 7 Appendices

## 7.1 Appendix 1: RFM transition table 2016-2017

| | About To Sleep | At Risk | Champions | Hibernating | Loyal Customers | Others | Potential Loyalist |
|---|---|---|---|---|---|---|---|
| About To Sleep | 0.00000000 | 0.04255319 | 0.06382979 | 0.72340426 | 0.02127660 | 0.06382979 | 0.08510638 |
| Champions | 0.00000000 | 0.10869565 | 0.54347826 | 0.02173913 | 0.21739130 | 0.08695652 | 0.02173913 |
| Hibernating | 0.02857143 | 0.02857143 | 0.08571429 | 0.60000000 | 0.20000000 | 0.02857143 | 0.02857143 |
| Loyal Customers | 0.00000000 | 0.00000000 | 0.29411765 | 0.11764706 | 0.35294118 | 0.23529412 | 0.00000000 |
| Others | 0.00000000 | 0.06000000 | 0.10000000 | 0.08000000 | 0.24000000 | 0.50000000 | 0.02000000 |
| Potential Loyalist | 0.00000000 | 0.06666667 | 0.10000000 | 0.30000000 | 0.23333333 | 0.20000000 | 0.10000000 |

## 7.2 Appendix 2: RFM transition table 2015-2016

| | About To Sleep | Champions | Hibernating | Loyal Customers | Others | Potential Loyalist |
|---|---|---|---|---|---|---|
| About To Sleep | 0.48571429 | 0.02857143 | 0.25714286 | 0.02857143 | 0.02857143 | 0.17142857 |
| At Risk | 0.00000000 | 0.00000000 | 0.00000000 | 0.00000000 | 1.00000000 | 0.00000000 |
| Champions | 0.06818182 | 0.45454545 | 0.04545455 | 0.15909091 | 0.15909091 | 0.11363636 |
| Hibernating | 0.32558140 | 0.04651163 | 0.51162791 | 0.00000000 | 0.09302326 | 0.02325581 |
| Loyal Customers | 0.05882353 | 0.38235294 | 0.11764706 | 0.20588235 | 0.05882353 | 0.17647059 |
| Others | 0.07692308 | 0.15384615 | 0.03846154 | 0.05769231 | 0.53846154 | 0.13461538 |
| Potential Loyalist | 0.23529412 | 0.11764706 | 0.00000000 | 0.05882353 | 0.17647059 | 0.41176471 |

## 7.3 Appendix 3: RFM transition table 2014-2015

| | About To Sleep | Champions | Hibernating | Loyal Customers | Others | Potential Loyalist |
|---|---|---|---|---|---|---|
| About To Sleep | 0.28571429 | 0.08571429 | 0.42857143 | 0.05714286 | 0.11428571 | 0.02857143 |
| Champions | 0.03448276 | 0.46551724 | 0.06896552 | 0.22413793 | 0.17241379 | 0.03448276 |
| Hibernating | 0.22580645 | 0.00000000 | 0.61290323 | 0.06451613 | 0.06451613 | 0.03225806 |
| Loyal Customers | 0.12500000 | 0.25000000 | 0.16666667 | 0.29166667 | 0.16666667 | 0.00000000 |
| Others | 0.11940299 | 0.13432836 | 0.10447761 | 0.11940299 | 0.40298507 | 0.11940299 |
| Potential Loyalist | 0.35714286 | 0.07142857 | 0.07142857 | 0.10714286 | 0.07142857 | 0.32142857 |

## 7.4 Appendix 4: Linear Regression Model, Train and Test Results

Call:
lm(formula = rfm_score ~ Contributie + Gift + Noodhulp, data = train)

Residuals:

```
   Min      1Q  Median      3Q     Max
-7.7920 -3.4488 -0.4488  3.5512  8.9346
```

```
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  8.40868    0.26623  31.584  < 2e-16 ***
Contributie -2.34326    0.30142  -7.774 1.74e-14 ***
Gift         2.38337    0.27262   8.742  < 2e-16 ***
Noodhulp    -0.05447    0.81676  -0.067    0.947
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3.704 on 1103 degrees of freedom
Multiple R-squared:  0.08148,	Adjusted R-squared:  0.07898
F-statistic: 32.62 on 3 and 1103 DF,  p-value: < 2.2e-16


Call:
lm(formula = rfm_score ~ Contributie + Gift + Noodhulp, data = test)

Residuals:
    Min      1Q  Median      3Q     Max
-5.9556 -2.8336 -0.9561  3.0444  7.1664

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   9.0781     0.5117  17.740  < 2e-16 ***
Contributie  -3.1220     0.5863  -5.325 2.11e-07 ***
Gift          1.8776     0.5232   3.588 0.000394 ***
Noodhulp      1.6664     2.5637   0.650 0.516256
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3.606 on 273 degrees of freedom
Multiple R-squared:  0.1026, Adjusted R-squared:  0.09273
F-statistic:  10.4 on 3 and 273 DF,  p-value: 1.671e-06
```

## 7.5 Appendix 5: Technical explanation of HMM

The initial values for $q_{11} - q_{44}$ are 0.1 as to avoid numerical overflow but also to allow each transition to be as likely as the next. Further the observed data is in a variable named rfm_score and the measurement times is in Year, and subject identifies are in Customer_id. The call to msm to estimate the parameters of the basic HMM were *msm(rfm_score~ Year, subject = customer_id, data = panel_data1, qmatrix = rbind( c(0, 0.1, 0.1, 0.1), c(0.1, 0, 0.1, 0.1), c(0.1, 0.1, 0, 0.1), c(0.1, 0.1, 0.1, 0)), hmodel = list hmmNorm(mean=4, sd=1), hmmNorm(mean=8.3, sd=3), hmmNorm(mean=12.5, sd=1), hmmNorm(mean=14.5, sd=1))*

When applying the direct mailing campaigns certain constraints were added to the parameters, such as the hcontraint. The hcontraint specifies which hidden Markov model parameters are constrained to be equal, meaning that for the three different direct mailing campaigns the effect should be equal across each state. So for example for Gift it looked like this: *hcovariates = list(~Gift, ~Gift, ~Gift, ~Gift)*.

## 7.6 Appendix 6: Basic HMM training and test results

Training

```
Call:
msm(formula = rfm_score ~ Year, subject = customer_id, data = train2,     qmatrix = Qhmm,
hmodel = list(hmmNorm(mean = 8, sd = 3),         hmmNorm(mean = 11.5, sd = 1),
hmmNorm(mean = 4, sd = 1),         hmmNorm(mean = 14, sd = 1)), hcovinits = list(-8, -8,         -
8, -8), control = list(fnscale = 3000, maxit = 5000))

Maximum likelihood estimates

Transition intensities
                  Baseline
State 1 - State 1 -0.7501459 (-1.005e+00, -0.5598)
State 1 - State 2  0.3354936 ( 2.139e-01,  0.5261)
State 1 - State 3  0.4097095 ( 2.946e-01,  0.5698)
State 1 - State 4  0.0049428 ( 2.302e-07,106.1078)
State 2 - State 1  0.6614987 ( 2.079e-01,  2.1043)
State 2 - State 2 -1.5392838 (-5.962e+00, -0.3974)
State 2 - State 3  0.0030742 ( 6.164e-08,153.3230)
State 2 - State 4  0.8747109 ( 1.674e-01,  4.5718)
State 3 - State 1  0.3000393 ( 1.728e-01,  0.5209)
State 3 - State 2  0.0017727 ( 2.291e-08,137.1564)
State 3 - State 3 -0.3025672 (-5.190e-01, -0.1764)
State 3 - State 4  0.0007552 ( 1.272e-09,448.2804)
```

```
State 4 - State 1  0.0168250 ( 7.000e-07,404.3969)
State 4 - State 2  1.2496507 ( 5.298e-01,  2.9475)
State 4 - State 3  0.0016775 ( 3.396e-09,828.6634)
State 4 - State 4 -1.2681533 (-2.932e+00, -0.5485)

Hidden Markov model, 4 states
State 1 - normal distribution
Parameters:
     Estimate      LCL      UCL
mean 8.381835 8.077555 8.686115
sd   3.247291 3.063692 3.441892

State 2 - normal distribution
Parameters:
      Estimate        LCL       UCL
mean 12.655457 11.8652608 13.445654
sd    0.909684  0.4005318  2.066066

State 3 - normal distribution
Parameters:
      Estimate       LCL      UCL
mean 4.2057431 4.0493177 4.362168
sd   0.9161902 0.8081685 1.038650

State 4 - normal distribution
Parameters:
      Estimate        LCL        UCL
mean 14.657139 14.1204351 15.1938430
sd    0.479674  0.2953422  0.7790525


-2 * log-likelihood:  5364.445
```

Test

```
Call:
msm(formula = rfm_score ~ Year, subject = customer_id, data = test2,     qmatrix = Qhmm, hmodel = list(hmmNorm(mean = 8, sd = 3),         hmmNorm(mean = 11.5, sd = 1), hmmNorm(mean = 4, sd = 1),         hmmNorm(mean = 14, sd = 1)), hcovinits = list(-8, -8,         -8, -8), control = list(fnscale = 3000, maxit = 5000))
```

```
Maximum likelihood estimates

Transition intensities
                  Baseline
State 1 - State 1 -2.228833 (-1.160e+01,-4.281e-01)
State 1 - State 2  0.714912 ( 4.856e-02, 1.052e+01)
State 1 - State 3  1.035081 ( 2.656e-01, 4.033e+00)
State 1 - State 4  0.478840 ( 8.030e-02, 2.856e+00)
State 2 - State 1  0.015777 ( 4.950e-11, 5.028e+06)
State 2 - State 2 -0.080758 (-9.408e+01,-6.932e-05)
State 2 - State 3  0.013322 ( 7.395e-12, 2.400e+07)
State 2 - State 4  0.051659 ( 1.253e-05, 2.129e+02)
State 3 - State 1  0.006014 ( 2.796e-10, 1.294e+05)
State 3 - State 2  0.006683 ( 2.293e-10, 1.947e+05)
State 3 - State 3 -0.015519 (-3.631e+02,-6.633e-07)
State 3 - State 4  0.002822 ( 1.508e-10, 5.281e+04)
State 4 - State 1  0.003716 ( 2.072e-10, 6.666e+04)
State 4 - State 2  0.006272 ( 3.369e-10, 1.168e+05)
State 4 - State 3  0.002724 ( 1.271e-10, 5.838e+04)
State 4 - State 4 -0.012712 (-3.450e+02,-4.684e-07)

Hidden Markov model, 4 states
State 1 - normal distribution
Parameters:
     Estimate      LCL      UCL
mean 7.916411 6.969955 8.862866
sd   3.647756 3.045127 4.369643

State 2 - normal distribution
Parameters:
     Estimate      LCL       UCL
mean 9.966977 8.197867 11.736086
sd   1.997639 1.064238  3.749687

State 3 - normal distribution
Parameters:
      Estimate       LCL      UCL
mean 4.3690263 3.9802413 4.757811
sd   0.9586375 0.6872175 1.337256
```

State 4 - normal distribution
Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 13.565387 | 12.6848417 | 14.44593 |
| sd | 1.210484 | 0.7586971 | 1.93130 |

-2 * log-likelihood:  668.8979

## 7.7 Appendix 7: Gift HMM

Call:

msm(formula = rfm_score ~ Year, subject = customer_id, data = panel_data1,     qmatrix = Qhmm, hmodel = hmodel1, hcovariates = list(~Gift,          ~Gift, ~Gift, ~Gift), hcovinits = list(-8, -8, -8, -8),     hconstraint = list(Gift = c(1, 1, 1, 1)), control = list(fnscale = 300,          maxit = 500))

Maximum likelihood estimates

Baselines are with covariates set to their means

Transition intensities

| | Baseline |
|---|---|
| State 1 - State 1 | -0.7883 (-1.070e+00,-5.810e-01) |
| State 1 - State 2 | 0.05914 ( 1.904e-02, 1.836e-01) |
| State 1 - State 3 | 0.4004 ( 2.964e-01, 5.408e-01) |
| State 1 - State 4 | 0.3288 ( 1.871e-01, 5.778e-01) |
| State 2 - State 1 | 0.04635 ( 4.094e-04, 5.247e+00) |
| State 2 - State 2 | -0.04835 (-4.631e+00,-5.048e-04) |
| State 2 - State 3 | 0.0004438 ( 3.026e-14, 6.509e+06) |
| State 2 - State 4 | 0.001560 ( 2.395e-12, 1.016e+06) |
| State 3 - State 1 | 0.3105 ( 1.991e-01, 4.843e-01) |
| State 3 - State 2 | 0.00008397 ( 2.459e-15, 2.867e+06) |
| State 3 - State 3 | -0.3125 (-4.708e-01,-2.074e-01) |
| State 3 - State 4 | 0.001839 ( 2.048e-12, 1.651e+06) |

State 4 - State 1  0.6926 ( 3.642e-01, 1.317e+00)

State 4 - State 2  0.06106 ( 1.681e-03, 2.218e+00)

State 4 - State 3  0.0004583 ( 5.613e-16, 3.743e+08)

State 4 - State 4 -0.7542 (-1.419e+00,-4.007e-01)

Hidden Markov model, 4 states

State 1 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 8.3614367 | 8.0811104 | 8.6417630 |
| sd | 3.1386264 | 2.9723228 | 3.3142348 |
| Gift | 0.4040601 | 0.1578054 | 0.6503149 |

State 2 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 14.0789939 | 13.8087625 | 14.3492252 |
| sd | 0.8700691 | 0.7096409 | 1.0667652 |
| Gift | 0.4040601 | 0.1578054 | 0.6503149 |

State 3 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 4.1172777 | 3.9838010 | 4.2507544 |
| sd | 0.8964817 | 0.7993001 | 1.0054790 |
| Gift | 0.4040601 | 0.1578054 | 0.6503149 |

State 4 - normal distribution

Parameters:

Estimate LCL UCL

mean 12.2189336 11.6698900 12.7679772

sd 1.4181971 1.1273351 1.7841039

Gift 0.4040601 0.1578054 0.6503149

-2 * log-likelihood: 6867.781

## 7.8 Appendix 8: Contribution HMM

Call:

msm(formula = rfm_score ~ Year, subject = customer_id, data = panel_data1, qmatrix = Qhmm, hmodel = hmodel1, hcovariates = list(~Contributie, ~Contributie, ~Contributie, ~Contributie), hcovinits = list(-8, -8, -8, -8), hconstraint = list(Contributie = c(1, 1, 1, 1)), control = list(fnscale = 3000, maxit = 5000))

Maximum likelihood estimates

Baselines are with covariates set to their means

Transition intensities

```
                  Baseline
State 1 - State 1 -0.7660922 (-1.038e+00, -0.565532)
State 1 - State 2  0.3428153 ( 1.976e-01,  0.594659)
State 1 - State 3  0.3773379 ( 2.808e-01,  0.507043)
State 1 - State 4  0.0459390 ( 1.096e-02,  0.192582)
State 2 - State 1  0.7833446 ( 4.178e-01,  1.468547)
State 2 - State 2 -0.8859422 (-1.635e+00, -0.480005)
State 2 - State 3  0.0034475 ( 2.383e-07, 49.881580)
State 2 - State 4  0.0991501 ( 7.103e-03,  1.384027)
State 3 - State 1  0.3029655 ( 1.811e-01,  0.506923)
State 3 - State 2  0.0063374 ( 2.185e-07,183.832817)
State 3 - State 3 -0.3098691 (-4.705e-01, -0.204090)
State 3 - State 4  0.0005661 ( 3.710e-08,  8.638851)
State 4 - State 1  0.0553374 ( 7.964e-04,  3.845036)
```

State 4 - State 2 0.0064985 ( 3.706e-07,113.960789)

State 4 - State 3 0.0027456 ( 1.315e-07, 57.315414)

State 4 - State 4 -0.0645814 (-2.694e+00, -0.001548)

Hidden Markov model, 4 states

State 1 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 8.2894767 | 8.0110180 | 8.56793545 |
| sd | 3.1367531 | 2.9716509 | 3.31102819 |
| Contributie | -0.3730566 | -0.7630566 | 0.01694347 |

State 2 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 12.4529921 | 11.9429785 | 12.96300566 |
| sd | 1.3222532 | 1.0319638 | 1.69420056 |
| Contributie | -0.3730566 | -0.7630566 | 0.01694347 |

State 3 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 4.1797192 | 4.0320795 | 4.32735886 |
| sd | 0.8681836 | 0.7765253 | 0.97066095 |
| Contributie | -0.3730566 | -0.7630566 | 0.01694347 |

State 4 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 14.2508659 | 13.9822335 | 14.51949833 |
| sd | 0.8345183 | 0.6680823 | 1.04241772 |

Contributie -0.3730566 -0.7630566  0.01694347

-2 * log-likelihood:  6875.545

## 7.9 Appendix 9: Emergency Aid HMM

Call:

msm(formula = rfm_score ~ Year, subject = customer_id, data = panel_data1, qmatrix = Qhmm, hmodel = hmodel1, hcovariates = list(~Noodhulp, ~Noodhulp, ~Noodhulp, ~Noodhulp), hcovinits = list(-8, -8, -8, -8), hconstraint = list(Noodhulp = c(1, 1, 1, 1)), control = list(fnscale = 300, maxit = 500))

Maximum likelihood estimates

Baselines are with covariates set to their means

Transition intensities

Baseline

State 1 - State 1 -7.635e-01 (-1.030e+00,-5.660e-01)

State 1 - State 2  3.271e-01 ( 1.890e-01, 5.663e-01)

State 1 - State 3  3.828e-01 ( 2.850e-01, 5.141e-01)

State 1 - State 4  5.363e-02 ( 1.641e-02, 1.753e-01)

State 2 - State 1  7.166e-01 ( 3.839e-01, 1.338e+00)

State 2 - State 2 -7.877e-01 (-1.470e+00,-4.222e-01)

State 2 - State 3  1.456e-04 ( 2.755e-24, 7.699e+15)

State 2 - State 4  7.102e-02 ( 2.277e-03, 2.215e+00)

State 3 - State 1  3.132e-01 ( 2.064e-01, 4.753e-01)

State 3 - State 2  6.340e-04 ( 8.716e-20, 4.612e+12)

State 3 - State 3 -3.139e-01 (-4.702e-01,-2.095e-01)

State 3 - State 4  2.932e-05 ( 2.674e-23, 3.215e+13)

State 4 - State 1  5.011e-02 ( 3.327e-04, 7.550e+00)

State 4 - State 2  3.761e-04 ( 4.167e-23, 3.395e+15)

State 4 - State 3  1.786e-04 ( 2.989e-20, 1.068e+12)

State 4 - State 4 -5.067e-02 (-7.277e+00,-3.528e-04)

Hidden Markov model, 4 states

State 1 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 8.3208582 | 8.041160 | 8.600556 |
| sd | 3.1568172 | 2.991202 | 3.331602 |
| Noodhulp | -0.2655869 | -2.224905 | 1.693732 |

State 2 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 12.3728487 | 11.830493 | 12.915204 |
| sd | 1.3818927 | 1.089238 | 1.753178 |
| Noodhulp | -0.2655869 | -2.224905 | 1.693732 |

State 3 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 4.1122426 | 3.9810589 | 4.2434263 |
| sd | 0.8640494 | 0.7716359 | 0.9675307 |
| Noodhulp | -0.2655869 | -2.2249055 | 1.6937316 |

State 4 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 14.2007920 | 13.9500364 | 14.451548 |
| sd | 0.8428925 | 0.6818421 | 1.041983 |
| Noodhulp | -0.2655869 | -2.2249055 | 1.693732 |

-2 * log-likelihood:  6878.741

## 7.10 Appendix 10: Robustness test of RFM

Contribution mailing – Large sample

| | About To Sleep | At Risk | Champions | Hibernating | Loyal Customers | Others | Potential Loyalist |
|---|---|---|---|---|---|---|---|
| About To Sleep | 0.046511628 | 0.023255814 | 0.104651163 | 0.034883721 | 0.058139535 | 0.209302326 | 0.523255814 |
| At Risk | 0.086956522 | 0.007496252 | 0.235382309 | 0.118440780 | 0.194902549 | 0.277361319 | 0.079460270 |
| Champions | 0.054554080 | 0.003320683 | 0.377134725 | 0.049335863 | 0.148007590 | 0.280834915 | 0.086812144 |
| Hibernating | 0.232985122 | 0.006964229 | 0.042735043 | 0.284900285 | 0.061095283 | 0.270655271 | 0.100664767 |
| Loyal Customers | 0.111607143 | 0.010602679 | 0.235491071 | 0.129464286 | 0.164062500 | 0.263950893 | 0.084821429 |
| Others | 0.074987418 | 0.004529441 | 0.096124811 | 0.080523402 | 0.084549572 | 0.574735783 | 0.084549572 |
| Potential Loyalist | 0.103813559 | 0.002118644 | 0.082627119 | 0.055084746 | 0.088983051 | 0.192796610 | 0.474576271 |

Gift Mailing – Large sample

| | About To Sleep | At Risk | Champions | Hibernating | Loyal Customers | Others | Potential Loyalist |
|---|---|---|---|---|---|---|---|
| About To Sleep | 0.111111111 | 0.037037037 | 0.185185185 | 0.000000000 | 0.074074074 | 0.222222222 | 0.370370370 |
| At Risk | 0.090620032 | 0.006359300 | 0.232114467 | 0.122416534 | 0.198728140 | 0.268680445 | 0.081081081 |
| Champions | 0.055944056 | 0.003496503 | 0.384115884 | 0.046953047 | 0.149850150 | 0.272227772 | 0.087412587 |
| Hibernating | 0.230846774 | 0.007392473 | 0.041666667 | 0.288978495 | 0.060819892 | 0.269153226 | 0.101142473 |
| Loyal Customers | 0.107482185 | 0.010688836 | 0.243467933 | 0.131828979 | 0.163301663 | 0.261282660 | 0.081947743 |
| Others | 0.080399061 | 0.004694836 | 0.087441315 | 0.088028169 | 0.083920188 | 0.575704225 | 0.079812207 |
| Potential Loyalist | 0.100000000 | 0.006250000 | 0.087500000 | 0.050000000 | 0.084375000 | 0.181250000 | 0.490625000 |

## 7.11 Appendix 11: Robustness test of HMM when removing recency

Basic Model

Call:

msm(formula = rfm_score ~ Year, subject = customer_id, data = panel_data1, qmatrix = Qhmm, hmodel = list(hmmNorm(mean = 5, sd = 3), hmmNorm(mean = 8, sd = 1), hmmNorm(mean = 3, sd = 1), hmmNorm(mean = 9, sd = 1)), control = list(fnscale = 6000, maxit = 5000))

Maximum likelihood estimates

Transition intensities

Baseline

```
State 1 - State 1 -13.276534 (-2.394e+09,-7.364e-08)
State 1 - State 2   6.324001 ( 3.438e-08, 1.163e+09)
State 1 - State 3   5.458889 ( 2.821e-08, 1.057e+09)
State 1 - State 4   1.493643 ( 1.137e-08, 1.963e+08)
State 2 - State 1   0.015941 ( 7.516e-12, 3.381e+07)
State 2 - State 2  -0.345527 (-6.346e-01,-1.881e-01)
State 2 - State 3   0.204530 ( 9.331e-02, 4.483e-01)
State 2 - State 4   0.125055 ( 6.355e-02, 2.461e-01)
State 3 - State 1   0.009902 ( 2.247e-06, 4.364e+01)
State 3 - State 2   0.294662 ( 2.054e-01, 4.227e-01)
State 3 - State 3  -0.305631 (-4.222e-01,-2.213e-01)
State 3 - State 4   0.001067 ( 1.838e-07, 6.190e+00)
State 4 - State 1   0.004460 ( 1.299e-06, 1.531e+01)
State 4 - State 2   0.337779 ( 1.913e-01, 5.965e-01)
State 4 - State 3   0.001706 ( 3.630e-07, 8.016e+00)
State 4 - State 4  -0.343945 (-5.988e-01,-1.976e-01)

Hidden Markov model, 4 states
State 1 - normal distribution
Parameters:
     Estimate      LCL      UCL
mean 5.088536 4.822814 5.354258
sd   2.631253 2.449974 2.825947

State 2 - normal distribution
Parameters:
     Estimate      LCL      UCL
mean 6.143122 5.887378 6.398866
sd   1.904202 1.744453 2.078580

State 3 - normal distribution
```

Parameters:

```
     Estimate       LCL       UCL
mean 2.5154176 2.4516587 2.5791765
sd   0.5354002 0.4881274 0.5872512
```

State 4 - normal distribution

Parameters:

```
    Estimate       LCL       UCL
mean 9.643059 9.5345943 9.7515245
sd   0.501826 0.4172146 0.6035966
```

-2 * log-likelihood:  5800.857

<u>Gift</u>

Call:

msm(formula = rfm_score ~ Year, subject = customer_id, data = panel_data1,     qmatrix = Qhmm, hmodel = hmodel1, hcovariates = list(~Gift,         ~Gift, ~Gift, ~Gift), hcovinits = list(-8, -8, -8, -8),     hconstraint = list(Gift = c(1, 1, 1, 1)), control = list(fnscale = 6000,         maxit = 5000))

Maximum likelihood estimates

Baselines are with covariates set to their means

Transition intensities

```
                  Baseline
State 1 - State 1 -11.856603 (-4.405e+06,-3.191e-05)
State 1 - State 2   5.631937 ( 1.504e-05, 2.109e+06)
State 1 - State 3   4.880241 ( 1.240e-05, 1.921e+06)
State 1 - State 4   1.344426 ( 4.433e-06, 4.077e+05)
State 2 - State 1   0.014419 ( 5.133e-10, 4.050e+05)
```

State 2 - State 2  -0.348134 (-5.726e-01,-2.117e-01)

State 2 - State 3   0.209074 ( 1.115e-01, 3.921e-01)

State 2 - State 4   0.124641 ( 6.521e-02, 2.382e-01)

State 3 - State 1   0.010477 ( 3.603e-06, 3.046e+01)

State 3 - State 2   0.294476 ( 2.045e-01, 4.240e-01)

State 3 - State 3  -0.306203 (-4.234e-01,-2.214e-01)

State 3 - State 4   0.001250 ( 4.044e-07, 3.866e+00)

State 4 - State 1   0.004817 ( 1.889e-06, 1.228e+01)

State 4 - State 2   0.339029 ( 1.925e-01, 5.971e-01)

State 4 - State 3   0.001960 ( 7.294e-07, 5.265e+00)

State 4 - State 4  -0.345806 (-5.997e-01,-1.994e-01)

Hidden Markov model, 4 states

State 1 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 5.1009918 | 4.83563774 | 5.3663459 |
| sd | 2.6201632 | 2.43881681 | 2.8149942 |
| Gift | 0.0764553 | -0.05005226 | 0.2029629 |

State 2 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 6.1554256 | 5.89946455 | 6.4113866 |
| sd | 1.8964775 | 1.73555105 | 2.0723256 |
| Gift | 0.0764553 | -0.05005226 | 0.2029629 |

State 3 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 2.5183678 | 2.45330802 | 2.5834276 |

sd   0.5431959  0.49306099 0.5984286

Gift 0.0764553 -0.05005226 0.2029629

State 4 - normal distribution

Parameters:

Estimate LCL UCL

mean 9.6325410  9.52644616 9.7386358

sd   0.4962511  0.41584247 0.5922079

Gift 0.0764553 -0.05005226 0.2029629

-2 * log-likelihood:  5799.474

<u>Contribution</u>

Call:

msm(formula = rfm_score ~ Year, subject = customer_id, data = panel_data1, qmatrix = Qhmm, hmodel = hmodel1, hcovariates = list(~Contributie, ~Contributie, ~Contributie, ~Contributie), hcovinits = list(-8, -8, -8, -8), hconstraint = list(Contributie = c(1, 1, 1, 1)), control = list(fnscale = 2000, maxit = 5000))

Maximum likelihood estimates

Baselines are with covariates set to their means

Transition intensities

Baseline

State 1 - State 1 -1.893e+01 (-1.296e+22,-2.766e-20)

State 1 - State 2  7.801e+00 ( 9.980e-21, 6.098e+21)

State 1 - State 3  8.992e+00 ( 1.301e-20, 6.217e+21)

State 1 - State 4  2.139e+00 ( 5.227e-21, 8.750e+20)

State 2 - State 1  4.858e-03 ( 3.502e-08, 6.740e+02)

State 2 - State 2 -3.011e-01 (-4.138e-01,-2.191e-01)

State 2 - State 3  2.957e-01 ( 2.115e-01, 4.135e-01)

State 2 - State 4  5.452e-04 ( 4.032e-09, 7.372e+01)
State 3 - State 1  1.095e-02 ( 8.762e-24, 1.368e+19)
State 3 - State 2  2.075e-01 ( 6.799e-02, 6.334e-01)
State 3 - State 3 -3.451e-01 (-7.880e-01,-1.511e-01)
State 3 - State 4  1.266e-01 ( 5.984e-02, 2.679e-01)
State 4 - State 1  2.048e-03 ( 1.576e-08, 2.661e+02)
State 4 - State 2  8.127e-04 ( 5.350e-09, 1.235e+02)
State 4 - State 3  3.450e-01 ( 2.001e-01, 5.948e-01)
State 4 - State 4 -3.479e-01 (-5.960e-01,-2.030e-01)

Hidden Markov model, 4 states

State 1 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 5.1094845 | 4.84289124 | 5.3760777 |
| sd | 2.6295035 | 2.44830635 | 2.8241110 |
| Contributie | 0.1418039 | -0.01769089 | 0.3012986 |

State 2 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 2.4991737 | 2.43190129 | 2.5664461 |
| sd | 0.5402935 | 0.49192286 | 0.5934204 |
| Contributie | 0.1418039 | -0.01769089 | 0.3012986 |

State 3 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 6.1565469 | 5.90410729 | 6.4089865 |
| sd | 1.9007193 | 1.74098984 | 2.0751034 |
| Contributie | 0.1418039 | -0.01769089 | 0.3012986 |

State 4 - normal distribution

Parameters:

| | Estimate | LCL | UCL |
|---|---|---|---|
| mean | 9.6488713 | 9.55010450 | 9.7476381 |
| sd | 0.4854125 | 0.41050942 | 0.5739826 |
| Contributie | 0.1418039 | -0.01769089 | 0.3012986 |

-2 * log-likelihood: 5797.621