



Fabian Peter Pribahnsnik, BSc.

Let the data tell us their story

Machine learning with insurance policies

Master's Thesis

to achieve the university degree of

Master of Science

Financial and Actuarial Mathematics

submitted to

Vienna University of Technology

Institute of Statistics and Mathematical Methods in Economics

Supervisor

Univ.Prof. Dipl.-Math. Dr.rer.nat. Thorsten Rheinländer

Vienna, October 2017

Affidavit

I declare that I have authored this thesis independently, that I have not used other than the declared sources/resources, and that I have explicitly indicated all material which has been quoted either literally or by content from the sources used.

Date

Signature

Abstract

Insurance companies are facing a huge amount of regulations, including various guidelines addressing forecast scenario calculations for the policies in the portfolio. Taking the hundreds of thousands policies into account an average insurance company has in its portfolio one can easily see that these scenario calculations are very time consuming. Due to the rising number of policies and the very tight time schedule introduced with Solvency II insurance companies are looking for ways to reduce the computational time significantly. In the past years different approaches were developed and already used for grouping similar policies together and therefore reducing the computation time. The currently used algorithms are ranging from just grouping policies with exactly the same attributes together to basic cluster algorithms like k-means. This work highlights potential problems with the algorithms currently used and shows the implementation of some machine learning techniques to accomplish the task of grouping.

Kurzfassung

Versicherungsunternehmen sehen sich mit einer immer größer werdenden Anzahl von Vorschriften konfrontiert. Ein Teil dieser Richtlinien beschäftigt sich dabei mit der Fragestellung wie Versicherungsportfolios in die Zukunft projiziert werden sollen. Bedenkt man dabei, dass ein durchschnittliches Versicherungsunternehmen hunderttausende von Polizzen im Bestand hat, kann man den Zeitaufwand erahnen, der für solche Prognoserechnungen aufzuwenden ist. Steigende Bestände von Versicherungspolizzen in Kombination mit engen aufsichtsrechtlich gesetzten Fristen führen dazu, dass Versicherungsunternehmen nach Möglichkeiten suchen, die Rechenzeit für Projektionen zu verkürzen. In den letzten Jahren wurden bereits verschiedene Ansätze entwickelt und zum Einsatz gebracht, um ähnliche Polizzen zusammenzufassen und damit die Rechenzeit zu verkürzen. Dabei reichen die derzeit verwendeten Methoden von einfachen Zusammenfassungen von Polizzen mit exakt gleichen Attributen bis hin zu Clusteralgorithmen wie beispielsweise k-means. Diese Arbeit zeigt mögliche Probleme mit den derzeit verwendeten Algorithmen auf und präsentiert neue Implementierungsansätze aus dem Bereich des maschinellen Lernens, um eine Gruppierung des Versicherungsbestandes noch effektiver umsetzen zu können.

Contents

Abstract	v
Kurzfassung	vi
1. Introduction	1
1.1. Problem formulation	3
1.2. Legal Framework	5
1.3. Statistical Learning	7
2. Sensitivities	9
2.1. Age	11
2.2. Technical interest rate	13
2.3. Duration	16
3. k-means	21
3.1. Elbow method - gap statistic	28
3.2. Silhouette method	30
3.3. Curse of dimensionality	34
4. Non-negative least squares (NNLS)	37
4.1. Numerical Aspects	44
4.2. QR - decomposition	48
4.2.1. Householder Transformation	49
4.2.2. Performance	53
A. Tables	59
B. Code	61

List of Figures

2.1.	Logarithm of the yearly mortality defined by the Austrian Annuity Valuation Table AVÖ 2005R Unisex.	11
2.2.	Yearly cash flow for claims depending on the age and the technical interest rate.	14
2.3.	Premiums depending on the age and the technical interest rate.	14
2.4.	Present value of future profits at time 0 depending on the age and the technical interest rate.	15
2.5.	Yearly reserve depending on the age and the technical interest rate.	15
2.6.	Yearly cash flow for claims depending on the duration and the age.	18
2.7.	Premiums depending on the duration and the age	18
2.8.	Present value of future profits at time 0 depending on the duration and the age.	19
2.9.	Yearly reserve depending on the duration and the age.	19
3.1.	Results for a three-cluster example: (a) raw data; (b) $k = 2$; (c) $k = 3$; (d) $k = 5$	27
3.2.	Three-cluster example: (a) Total within Sum of Squares; (b) Gap-Statistic	29
3.3.	Left: silhouette plot for $k = 3$; Right: silhouette plot for $k = 5$	33
4.1.	Development of the non-negative entries of the solution vector x based on the number of iterations.	42
4.2.	Development of the deviance based on the number of iterations.	43
4.3.	Mirroring of \vec{x} to $\vec{P}x$ through hyperplane H	51
4.4.	Computation time for solving the least squares problem $Ax = b$ in seconds.	57

Todo list

Weitere Details für jedes Kapitel folgen.	5
Make a cake	65
Figure: Make a sketch of the structure of a trebuchet.	65

1. Introduction

A fundamental problem faced by many insurance companies is the projection of the insurance portfolio into the future. In a projection, the future cash flows for each individual policy must be calculated on the basis of actuarial principles and then saved for further analysis. Depending on the purpose of the forecast, these cash flows have to be provided either on a monthly or annually basis. Together with the contractually agreed benefits to the policyholder, a wide variety of other parameters must also be taken into account and modeled in such projections. These include, for example, all contract changes that may occur during the duration of the contract, such as a premium pause, a surrender or the occurrence of a claim. While the calculation of a small set of policies over a relatively short time horizon does not pose a challenge in terms of computation time, this fact changes greatly when projecting entire portfolios. This problem is particularly severe for life insurance portfolios. These contracts often have durations of several decades and the portfolios tend to grow over time as fewer policyholders leave than new ones are added. Even with the optimistic assumption that the complete projection of a single contract only takes a hundredth of a second, the computing time adds up to several hours for a portfolio with several million policies. As the liabilities are projected over a period of several decades, it is also essential to simulate the development of the assets, underlying the liabilities, over this period. Even under the assumption that the assets can be represented by a small number of different types of investments, their projection additionally increases the run time of the projection. The simultaneous simulation of the asset and liability portfolios results in further factors that have to be taken into account with respect to the behavior of policyholders during the contract term. If one assumes that the policyholder behavior during the projection period also depends on external parameters such as the current interest rates on savings, one also has to include that effect into the simulation. This finally results in a dynamic interaction of all components which can be summarized in a simplified pseudo code given in algorithm 1:

Note that during an iteration (algorithm 1, 2a - 2d) all results must be kept in

1. Introduction

Algorithm 1 Simplified dynamic interaction scheme of portfolio projection

1. Initialisation of assets and liabilities at time $t = 0$.
 2. Iteration till the end of the projection horizon is reached:
 - a) Calculation of one time step for the liabilities. This means that all policies are projected to the next year ($t \mapsto t + 1$).
 - b) Calculation of one time step for the assets. This means that the returns of all investments are simulated for the next year.
 - c) Simulation of the dynamic policyholder behavior based on the current economic parameters from the previous step.
 - d) Application of pre-defined management decisions based on current developments in assets and liabilities. This means that in this step it is determined how high the dividend per share, for example, will be for this year.
-

memory until every decision for that loop is made and the next iteration starts. Assuming that there is a portfolio of several million policies and for each policy at least a few dozen variables are relevant for the decision making process, a memory requirement of at least hundreds of million individual values emerges. Also the simulations of the assets side and the subsequent management decisions have a considerable memory requirement. All this leads to the fact that the projection models currently used in the insurance industry are extremely demanding in terms of their memory requirements and execution time. There are at least two different ways to address this problem:

- Outsourcing of calculations to data centers.
- Data compression in the sense that similar policies are grouped together and only the grouped portfolio is calculated.

With the increasing availability of cloud services, it is already an option these days to outsource complex computing operations to specialized providers. It is possible to rent different types of computing capacities for a certain period of time without much effort and run the projections there. The big advantage of this option is that there is no need to set up, maintain and configure an infrastructure. Since personal data such as age or gender are always used in the projection of insurance contracts, potential problems could arise with respect to the General Data Protection Regulation [**datenschutz**]. Many companies have therefore decided to compress the insurance portfolio and therefore reducing the memory requirements using various techniques. It is then feasible

to calculate the projections with infrastructure that is owned by the company. This approach has the big advantage that it avoids possible problems with data protection issues and also reduces the dependency on external services. On the other hand, an additional effort has to be made to compress the portfolio in a proper way. Of course, it is of utmost importance that the compressed portfolio has the same characteristics and produces the same cash flows as the non-compressed one. Exactly here, this thesis kicks in and shows possible ways, how a portfolio of insurance contracts can be compressed.

1.1. Problem formulation

For the sake of simplicity all values calculated by the projection tool are referred to as cashflows regardless of whether they are non-cumulative values such as the reserve or actual cashflows such as the premium. The task is to find a portfolio with a reduced number of policies, the so called grouped portfolio, so that the projected cashflows match those from the reference portfolio as accurately as possible. In order to be able to define what accurately means in terms of cashflow deviations, some basic concepts must be defined first .

Definition 1.1. Let $\mathcal{V} = \{V, V \text{ is a valid insurance contract}\}$ be the set of all valid insurance contracts. A finite set of elements $P \subset \mathcal{V}$ is called a portfolio and the number of policies within that portfolio is determined by its cardinality.

Definition 1.2. Let $P \subset \mathcal{V}$ be a portfolio of n policies (i.e. $|P| = n$) and m the number of projected cashflows by the simulation s . Then the individual cashflows corresponding to P are encoded in $A \in \mathbb{R}^{m \times n}$ and the summed cashflows are encoded in $b \in \mathbb{R}^m$.

$$\begin{aligned} s : \mathcal{V} &\rightarrow \mathbb{R}^{m \times n} & s : \mathcal{V} &\rightarrow \mathbb{R}^m \\ P &\mapsto s(P) = A & P &\mapsto A \cdot \mathbb{1}_{n \times 1} = b \end{aligned}$$

Remark 1.1. It should be noted that the definition of portfolio is ambiguous. It can include anything from a single policy to all policies held by an insurance company. The usual segmentation into portfolios is often based on the following characteristics:

- All contracts of a single tariff are put into one portfolio.
- All contracts of a tariff group (endowment insurances, pension insurances,...) are put into one portfolio.

1. Introduction

- All contracts sold in the same country are put into one portfolio.

Example 1.1. Let $P \subset \mathcal{V}$ be a portfolio with $|P| = 1000$, the number of cashflows $m = 180$. Then the cashflows generated by the projection software can be described as:

$$A = \begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,1000} \\ a_{2,1} & \ddots & & a_{2,1000} \\ \vdots & & \ddots & \vdots \\ a_{180,1} & a_{180,2} & \cdots & a_{180,1000} \end{pmatrix} \quad b = \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_{180} \end{pmatrix} = \begin{pmatrix} \sum_{i=1}^{1000} a_{1,i} \\ \sum_{i=1}^{1000} a_{2,i} \\ \vdots \\ \sum_{i=1}^{1000} a_{180,i} \end{pmatrix}$$

A column in matrix A describes all cashflows generated by this policy. One row of matrix A describes the same cashflow generated by the different policies. By calculating line totals, the corresponding cashflow is obtained at portfolio level. The individual policy by policy cashflows are therefore given in matrix A , and the portfolio cash flows in vector b .

Definition 1.3. Let $P \subset \mathcal{V}$ be a portfolio with $|P| = n$, $\tilde{P} \subset \mathcal{V}$ the grouped portfolio with $|\tilde{P}| = \tilde{n}$, $\tilde{n} < n$ and $w \in \mathbb{R}_{\geq 0}^m = \{x \in \mathbb{R}^m, x \geq 0\}$ a vector of weights. Then the weighted sum of squares of the cashflows over the entire projection horizon between the grouped portfolio \tilde{P} and the ungrouped one P is given by:

$$WSS_{total} = \|w \circ (b - \tilde{b})\|_2^2 \quad (1.1)$$

The weighting parameter w makes it possible to make deviations from certain cashflows more or less important by weighting them differently. This can be useful, for example, to weight deviations at the end of the projection period less heavily compared to deviations at the beginning of the projection horizon. Particularly with projection horizons of 30 years and more, it may make sense to weight deviations in cashflows less strongly at a later point in time.

Remark 1.2. In a situation where every deviation of cashflows between the grouped and the ungrouped portfolio is equally important, the elements of w are all one. In this situation equation (1.1) simplifies to:

$$WSS_{total} = \|b - \tilde{b}\|_2^2 \quad (1.2)$$

The aim is to develop a method which is capable of finding a suitable grouped portfolio for each portfolio at hand so that (1.1) is sufficiently small. If there are several methods that come to similar results, then of course the one that needs the smallest grouped portfolio (i.e. smallest \tilde{n}) to generate the desired cash flows is of interest.

This thesis reviews the currently used technique for grouping policies together and introduces furthermore some new approaches on how life insurance policies can be grouped together. We will therefore highlight drawbacks and advantages with a special emphasis on the regulatory requirements of every approach discussed. Theoretical considerations as well as practical implementations and tests with real world data will provide us some information on which method an insurance company should work with in order to obtain the best grouping results.

This thesis is structured as follows: First we give an overview on the legal framework which lays down the minimum requirements for grouping-approaches in insurance companies and introduce the two types of statistical learning, namely supervised and unsupervised. We then discuss how sensitive main characteristics of a policy are with respect to the interest rate, the age or the duration to get a better understanding on which parameters are important for grouping purposes. We therefore make a sensitivity analysis with real world data and a widely used projection tool. In the next chapter we introduce the currently used unsupervised learning algorithm k-means and derive some theoretical findings.

Weitere Details
für jedes Kapitel
folgen.

1.2. Legal Framework

Solvency II - entered into force on 1 January 2016 - is the European framework for a common insurance supervision. It is intended to achieve a harmonization of the European insurance sector and was implemented in accordance with the Lamfalussy architecture which works on a 4 level basis [**Lamfalussy**'homepage]. The most significant elements and aims of the new regulation framework can be studied on the homepage of the financial market authority (FMA) [**FMA**'homepage] and on the homepage of the European Insurance and Occupational Pensions Authority (EIOPA) [**EIOPA**'homepage]. This work is intended not to cover all aspects and aims of the new Solvency II regulation framework but focuses on the topic of data quality regarding to

1. Introduction

the actuarial function. In order to meet all the requirements imposed by Solvency II, insurance companies need to process large amounts of data within a short period. One critical aspect of these calculations is the projection horizon which however should cover the full lifetime of all obligations as stated in [Time horizon]:

3.83.

The projection horizon used in the calculation of best estimate should cover the full lifetime of all obligations related to existing insurance and reinsurance contracts on the date of the valuation.

3.84.

The determination of the lifetime of insurance and reinsurance obligations shall be based on up-to-date and credible information and realistic assumptions about when the existing insurance and reinsurance obligations will be discharged or cancelled or expired.

Another aspect needed to be considered is the fact that cash flow calculations need to be done for a variety of different economic scenarios which yields to an enormous computational effort. Due to the tight time schedule, insurance companies are looking for new possibilities to speed up these time consuming calculations. One approach is not to make all these calculations on a per policy level, but on a grouped level where similar policies are grouped together and represented by only a few policies. This approach raises the question of how to maintain data quality as mentioned in the level 1 directive [Directive] while reducing the number of policies.

Article 82

Data quality and application of approximations, including case-by-case approaches, for technical provisions

Member States shall ensure that insurance and reinsurance undertakings have internal processes and procedures in place to ensure the appropriateness, completeness and accuracy of the data used in the calculation of their technical provisions...

By publishing the level 2 regulations, supplementing the level 1 directive [Directive] the European Commission is getting more specific on data quality (Article 19 in [Regulations]) and also formulates concrete requirements for grouped policies [Regulations].

Article 35

Homogeneous risk groups of life insurance obligations

The cash flow projections used in the calculation of best estimates for life insurance obligations shall be made separately for each policy. Where the separate calculation for each policy would be an undue burden on the insurance or reinsurance undertaking, it may carry out the projection by grouping policies, provided that the grouping complies with all of the following requirements:

- a) there are no significant differences in the nature and complexity of the risks underlying the policies that belong to the same group;
- b) the grouping of policies does not misrepresent the risk underlying the policies and does not misstate their expenses;
- c) the grouping of policies is likely to give approximately the same results for the best estimate calculation as a calculation on a per policy basis, in particular in relation to financial guarantees and contractual options included in the policies.

These level 2 regulations are a reference point on what to consider when grouping policies together and they are even further specified in the level 3 guidelines issued by EIOPA[**Guidelines'TP**]. Further details on the level 3 guidelines including feedback statements to the consultation paper (EIOPACP-14/036) and the guidelines can be obtained from [**Final'Report**].

1.3. Statistical Learning

Statistical learning refers to a set of methods which deals with predicting outcomes based on input variables or finding patterns in data sets. In order to accomplish the task of grouping together similar policies, different approaches from statistical learning can be applied. All these methods can be classified either as supervised or unsupervised. Within the framework of supervised methods, statistical models try to predict output variables y_i based on some input variables x_i where the relation $y = f(x)$ is unknown. It is therefore indispensable to have input as well as output data to parameterize such a model in order to find a prediction \hat{f} of f . Unsupervised methods, in contrast, are used when inputs x_i but no corresponding outputs y_i are available. These

1. Introduction

methods then try to find some hidden patterns within to data. The task of grouping insurance policies involves many different aspects. On the one hand we have all data needed to apply supervised methods, but on the other hand we are only interested in the patterns that can be revealed by an unsupervised method. The input variables are given by the characteristics of each policy and the corresponding output variables are determined by the projection tool. Our primary goal is not to get a good \hat{f} because the projection tool, which stands for f , is already known. We are more interested in hidden patterns that can be used for grouping purposes. In a first step we will apply unsupervised methods to the data and try to group the policies based on their characteristics and their cash flows. In a further step we will try to use the additional information of f to improve the grouping results if possible.

2. Sensitivities

Grouping together single policies and representing them by just a few representative ones always comes along with a loss of information. A natural question which arises when grouping insurance contracts together is how to determine the main characteristics of the new representative policy. Some characteristics should for technical reasons be defined as the sum of the individual ones, like the sum insured, the premium or the accumulated reserve. This is needed to guarantee the equality between the un-grouped and the grouped portfolio in terms of these characteristics at the beginning of the projection horizon. For other characteristics like the age, the duration or the gender it is not intuitively clear how they should be defined for a representative policy. Possible solutions which can be implemented easily range from taking the weighted average over the value with the highest relative frequency or to just taking the median of the grouped policies. Another difficulty which arises when grouping together policies from different product generations is, how the technical interest rate of the representative contract should be defined. Even if the policies are identical in terms of age, sex, sum insured, duration, costs,... and just differ on their issue date the huge possible differences with respect to the technical interest rate as shown in table 2.1 can have enormous impacts on the projected cash flows. Already a relative small difference in the technical interest of only one percent causes double digit differences in the guaranteed capital after 1 decade.

31.12. 1994	30.06. 2000	31.12. 2003	31.12. 2005	31.03. 2011	20.12. 2012	31.12. 2014	31.12. 2015	31.12. 2016
4%	3.25%	2.75%	2.25%	2%	1.75%	1.5%	1%	0.5%

Table 2.1.: Maximum technical interest rates for life insurance contracts issued after the given dates. (see [fakten'trends])

It is therefore important to know how sensitive the different output variables of interest which are calculated by the projection tool react if various input parameters are changed slightly. The most basic task is to determine whether the correlation between the input and output variables is positive or negative.

2. Sensitivities

There are many output variables which are important for determining if a grouping process has been successful in terms of accuracy or not, but in the subsequent we will focus only on a few of them, namely the premium, the present value of future profits at time 0, the reserve and the yearly claims. Due to the big variety of different insurance products we will just give some general guidelines based on the most important input variables. Most of the life insurance contracts can be built up by the following elementary insurance types and some additional factors for different types of costs.¹:

$$A_x = \sum_{k=0}^{\infty} v^{k+1} {}_k p_x q_{x+k} \quad (\text{Whole life insurance}) \quad (2.1)$$

$$A_{x:\overline{n}|}^1 = \sum_{k=0}^{n-1} v^{k+1} {}_k p_x q_{x+k} \quad (\text{Term insurance}) \quad (2.2)$$

$$A_{x:\overline{n}|} = \sum_{k=0}^{n-1} v^{k+1} {}_k p_x q_{x+k} + v^n {}_n p_x \quad (\text{Endowment}) \quad (2.3)$$

$$\ddot{a}_x = \sum_{k=0}^{\infty} v^k {}_k p_x \quad (\text{Whole life annuity}) \quad (2.4)$$

$$\ddot{a}_{x:\overline{n}|} = \sum_{k=0}^{n-1} \ddot{a}_{\overline{k+1}|} {}_k p_x q_{x+k} + \ddot{a}_{\overline{n}|} {}_n p_x \quad (\text{Temporary life annuity}) \quad (2.5)$$

These basic types already show that the main characteristics which should be taken care of, when it comes to a grouping process are the age x , the duration n and the technical interest rate which is implicitly given by v . The following graphs and analyses are based on an endowment policy with a duration of 25 years, a sum insured of 10.000 € and an investment return of 3% p.a. over the whole projection horizon. The duration of 25 years is in all subsequent considerations equal to the duration of the premium payments which are made on a yearly basis. All other parameters especially the lapse, paid-up and surrender rates as well as first and second order assumptions can't be given here in detail.

¹For detailed definitions and explanations see [**Gerber**].



Figure 2.1.: Logarithm of the yearly mortality defined by the Austrian Annuity Valuation Table AVÖ 2005R Unisex.

2.1. Age

The age of an insured person is one of the main factors which drives the projected outcome because it directly influences the probability of death and survival as shown in (2.1) - (2.5). When the age is changed from x to $x + 1$ the survival- and death-probabilities ${}_k p_x$ and ${}_k q_x$ change as well. It is impossible to predict in general whether the probabilities will rise or fall. Figure (2.1) shows, for example, the graph of logarithmic mortality rates based on the values of the unisex mortality table from the Actuarial Association of Austria [kainhofer2006new]. A high level of non-linearity can be observed, which naturally leads to greater challenges in the grouping.

As known from life tables it is a bit more likely to die just after birth than a bit afterwards and the same is true for people aged around 20. The exact ages where the probability of survival increases and the probability of death decreases when a person gets a year older depends heavily on the life table and the sex of the insured person. Whether the values for (2.1) - (2.5) will rise or

2. Sensitivities

fall when the age x is increased by 1 year will therefore depend on n , x and the sex of the insured person. To get a better insight into the portfolio, simulation runs for various parameters should be done. In figure (2.2) the development of the yearly total claims is plotted against the duration of 25 years. The claims are the amount of money that must be paid to the policyholder at the time of an insured event multiplied by the probability that such an event will occur. Such events can be of all kinds, but the most common are, for example, the death of the insured person or a surrender of the contract.

For a clearer chart the last cash flow which is the sum insured and therefore substantially larger than the yearly claims is omitted. We see that for younger people (green and red lines) the claims are almost identical in the first years and only deviate slightly at the end of the duration due to minor differences in the probabilities of death. For an insured person aged 60 we observe over the entire projection horizon considerably higher claims compared to younger policyholders. This gap between young and old policyholders which is mostly driven by mortality effects even increases with time. An insured person aged 60 which gets one year older faces in absolute values an higher increase in the mortality rate compared to an insured person aged 40 and so the claims will be higher in absolute values for the older person. This effect is partially compensated by lower surrender claims due to the higher mortality rates. If one compares the development of the claims also with respect to different interest rates, one can see in figure (2.2) that there are hardly any differences between the values of 2%, 3% and 4% shown.

In figure (2.3) the development of the booked premium at time 0 is plotted against the age. For policyholders aged between 15 and 30 the premium stays almost constant and then starts to increase exponentially. The increase of the premium is of exponential order due to the fact that the mortality rate is also increasing exponentially. Another fact that is not surprising is that the premium is the lower the higher the technical interest rate is, because the technical interest rate is used as a discount factor in (2.1) - (2.5). In figure (2.4) the present value of future profits (PVFP) at time 0 is plotted against the age. The PVFP is the higher the higher the entry age of the policyholder is, which is a counter intuitive relation at first sight. An analysis of the yearly cashflows for two different policyholders aged 15 and 70 reveals that this phenomenon is based on two different aspects as given in detail in table A.1.

1. When the guaranteed interest rate is roughly equal to the investment return or even higher then it is more advantageous for the insurance company when the policyholder is older and therefore dies earlier because

the difference between the guaranteed interest rate and the investment return need not to be financed over a long period. This leads to the observed fact that the PVFP is the lower the higher the technical interest rate is.

2. The differences of the first and second order assumptions of the mortality rates are in absolute values the bigger the higher the age is, because in almost all cases the second order assumptions of the mortality rates are just a fixed fraction of the first order assumptions. This directly leads to a higher risk margin and therefore to a higher premium for elder persons in absolute values as shown in column *prem_diff* in table A.1. The higher premium overcompensates the higher death claims and therefore increases the surplus in absolute values and leads to a higher present value of future profits.

In figure (2.5) the value of the reserve is plotted against the time. In all three cases the reserve is zero at the beginning and then starts to increase. This is due to the fact, that the valuation date of the projection is Q1 but the begin month of the policy is later. We see that for the ages of 15 and 30 the difference in the reserve is negligible for all different values of the technical interest rate. The reserve for a 45 year old person is almost identical to the one of younger policyholders at the first 10 years of the endowment but then increases at a slightly slower rate. For a person aged 60 we get a different picture because the reserve is not always monotonically increasing as it is true for the younger policyholders. The reserve increases after approximately 10 years at a much slower rate compared to the other policyholders and even starts to decrease after roughly 20 years. This effect can again be explained by the much higher morality rates in absolute values for older policyholders as time increases. Due to that fact the reserve is at the end of the projection horizon when the maturity claims are payed out for an older policyholder approximately half of the size as for a younger policyholder.

2.2. Technical interest rate

The technical interest rate is one of the key assumptions in the life insurance business. It determines the factor by which the reserve and the savings premium increases during the contract period. After the contract has been concluded the technical interest rate is fixed and can't be changed by the insurance company. The maximum technical interest rate has been reduced

2. Sensitivities



Figure 2.2.: Yearly cash flow for claims depending on the age and the technical interest rate.



Figure 2.3.: Premiums depending on the age and the technical interest rate.

2.2. Technical interest rate



Figure 2.4.: Present value of future profits at time 0 depending on the age and the technical interest rate.



Figure 2.5.: Yearly reserve depending on the age and the technical interest rate.

2. Sensitivities

dramatically by the Financial Market Authority in recent years from 4% to 0.5% as shown in table 2.1. The regulation of this upper bound is also relevant as it is often related to the minimum interest rate guaranteed to the policy holder. It is obvious that the higher the technical interest rate, the higher the guaranteed benefit or the lower the premium will be. When the grouping algorithm forces policies from different product generations with same payout characteristics but different technical interest rates to be grouped together one important thing to be aware of are sensitivities. Another important aspect which need to be taken care of when policies with different technical interest rates are grouped together is the one of consistent management rules. Take for example policy 1 with a technical interest rate of 2% and a bonus rate of 2% and policy 2 with a technical interest rate of 4% and a bonus rate of 0%. Lets assume that the two policies are similar and the grouped policy has a technical interest rate of 3% and a bonus rate of 1%. The total interest rate then is the same for the grouped and the ungrouped policies. Assume that the bonus rate is reduced by 1% caused by a management decision. Then policy 1 has only a bonus rate of 1% and policy 2 doesn't change at all, but the grouped policy has now a bonus rate of 0%. The total interest rate is not the same for the grouped and the ungrouped policies which can potentially have major impacts on the projected cash flows. When the technical interest rate increases, the present value of future profits as well as the premium will decrease as shown in figure (2.4) and (2.3) respectively. This behavior is not surprising at all, because as the technical interest rate rises the insurance company guarantees a higher benefit and this yields *ceteris paribus* to a lower PVFP. The reserve and the claims are not that much affected by an increase of the technical interest rate as shown in figure (2.2) and (2.5) respectively.

2.3. Duration

The duration n of an insurance contract is next to the age and the technical interest rate another main characteristic which need to be taken care of when a grouping process is carried out. In figure (2.6) the yearly claims except the last claim, which is the maturity claim, are shown for different ages. One obvious conclusion that can be derived is that the sum of all sorts of claims except the maturity claim is getting the higher the higher the age is. Another observation that can be made is that for any given time t the claims are the higher the shorter the duration gets when we keep the age fixed. This is not surprising at all, because a shorter duration goes along with a higher premium (see figure

(2.7)) and a higher reserve (see figure (2.9)) which yields to higher claims for every fixed t . In figure (2.7) we see that the premium is decreasing with an exponential order when the duration is increased. The difference between the premiums for policyholders with different ages is indistinguishable small for short term contracts and is getting bigger as duration increases. In figure (2.8) the present value of future profits at time 0 is plotted against the duration of the contract. We see the same effect as in figure (2.4) where contracts with higher ages lead to a higher PVFP. The effect of the absolute difference between the first and second order mortality assumptions is getting the bigger the longer the duration is and therefore the PVFP is getting the higher the longer the duration is. In the last sensitivity chart (2.9) the reserve is plotted against the time for different values of x and n . We see that for every time t the reserve is the higher the shorter the duration is, because a shorter duration leads, *ceteris paribus*, to a higher premium which then results in a higher reserve. For short term contracts up to 10 years the reserve is approximately the same across different ages and is then getting the lower the higher the age and the longer the duration is.

2. Sensitivities



Figure 2.6.: Yearly cash flow for claims depending on the duration and the age.

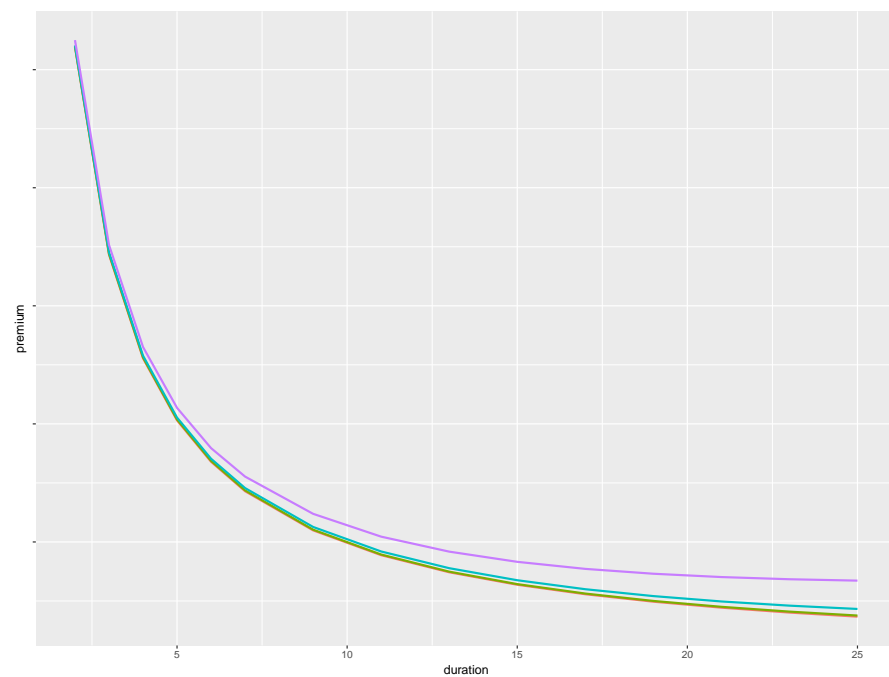


Figure 2.7.: Premiums depending on the duration and the age

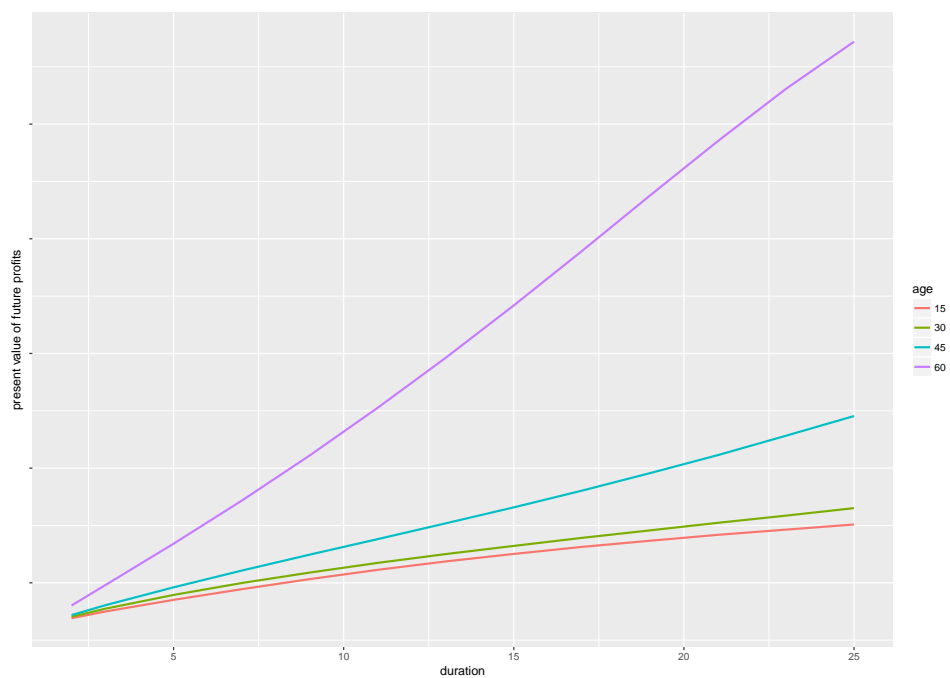


Figure 2.8.: Present value of future profits at time 0 depending on the duration and the age.

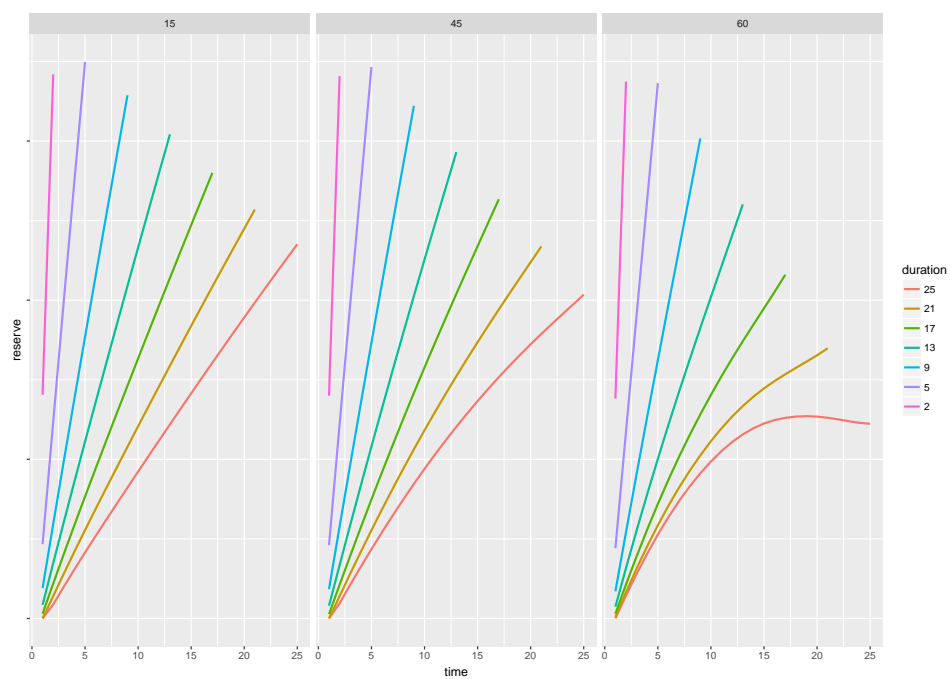


Figure 2.9.: Yearly reserve depending on the duration and the age.

3. k -means

To be able to process, summarize and understand huge amounts of data better, one is interested in methods that are able to find patterns in the data. The characteristics of these patterns then can be represented by just a few representative data points which behave like the whole data set. Given a data set the challenge is, based on a measure of similarity, to find groups of observations which are quite similar within each group but quite different to all the other groups. If this task has to be done with unlabeled data it is referred to as unsupervised clustering (c.f.[jain2010data]). One of the most widely used unsupervised clustering approaches is the k -means clustering. The k -means method is a simple approach in cluster analysis which splits a data set of n p -dimensional observations into k distinct clusters. Each observation belongs uniquely to exactly one of the k clusters, where k is a predefined number of clusters. Let $C = \{C_1, C_2 \dots, C_k\}$ denote the sets containing the indices of the observations related to the clusters, then we get:

Definition 3.1. Let $X = \{x_1, \dots, x_n\}$ be a data set. X is said to be partitioned into k different clusters $C_1, C_2 \dots, C_k$ if

$$(i) \ C = C_1 \cup C_2 \dots \cup C_k = \{1, \dots, n\}$$

$$(ii) \ C_i \cap C_j = \emptyset \quad \forall i \neq j$$

The basic idea of the k -means clustering is to minimize the variation within the clusters. For this purpose some distance measure is needed in order to be able to define variation within clusters.

Definition 3.2. Let X be a set, $d: X \times X \rightarrow \mathbb{R}$ a function. Then d is called a metric (or distance) on X if for all $x, y, z \in X$ the following conditions are fulfilled:

$$(D_1) \ d(x, y) = 0 \Leftrightarrow x = y \quad \text{(Identity of indiscernibles)}$$

$$(D_2) \ d(x, y) = d(y, x) \quad \text{(symmetry)}$$

$$(D_3) \ d(x, z) \leq d(x, y) + d(y, z) \quad \text{(triangle inequality)}$$

3. k -means

Remark 3.1. *Given the axioms from definition 3.2 it can be shown that a non-negativity property can be deducted e.g. $d(x, y) \geq 0 \forall x, y \in X$.*

$$\begin{aligned} d(x, y) + d(y, x) &\geq d(x, x) \\ d(x, y) + d(x, y) &\geq d(x, x) \\ 2d(x, y) &\geq 0 \\ d(x, y) &\geq 0 \end{aligned}$$

Example 3.1. (c.f. [analysis'1]) *The most common used distance functions for two points $x = (x_1, \dots, x_p)$ and $y = (y_1, \dots, y_p)$ in \mathbb{R}^p are:*

★ *Euclidean distance:*

$$d_2(x, y) := \sqrt{\sum_{j=1}^p (x_j - y_j)^2}$$

★ *Manhattan distance:*

$$d_1(x, y) := \sum_{j=1}^p |x_j - y_j|$$

★ *Chebyshev (maximum) distance:*

$$d_\infty(x, y) := \max_j |x_j - y_j|$$

★ *Minkowski distance (L^q distance) with $q \geq 1$:*

$$d_p(x, y) := \left(\sum_{j=1}^p (x_j - y_j)^q \right)^{\frac{1}{q}}$$

Typically the Euclidean distance is used as a measure of similarity to compute the distance between the different points. By using the Euclidean metric as a measure of similarity one assumes that the clusters are spherical.

Definition 3.3. *Let the Euclidean metric be the measure of similarity for the data points in the data set $X = \{x_1, \dots, x_n\}$ and p the dimension of the data. Then the variation within one cluster C_l , $l = 1, \dots, k$ is defined as:*

$$D(C_l) := \frac{1}{|C_l|} \sum_{j=1}^p \sum_{i, i' \in C_l} (x_{ij} - x_{i'j})^2$$

Remark 3.2. For the average over one dimension in one cluster we use the short notation $\bar{x}_{lj} = \frac{1}{|C_l|} \sum_{i \in C_l} x_{ij}$.

Remark 3.3. The identity $\sum_{i \in C_l} (x_{ij} - \bar{x}_{lj})^2 = (\sum_{i \in C_l} x_{ij}^2) - |C_l| \bar{x}_{lj}^2$ can be verified by simple calculus.

Corollary 3.1. The variation within one cluster, $D(C_l)$ can be written as:

$$D(C_l) = 2 \sum_{i \in C_l} \sum_{j=1}^p (x_{ij} - \bar{x}_{lj})^2 \quad (3.1)$$

Proof.

$$\begin{aligned} D(C_l) &= \frac{1}{|C_l|} \sum_{j=1}^p \sum_{i, i' \in C_l} (x_{ij} - x_{i'j})^2 \\ &= \frac{1}{|C_l|} \sum_{j=1}^p \sum_{i, i' \in C_l} x_{ij}^2 - 2x_{ij}x_{i'j} + x_{i'j}^2 \\ &= \sum_{j=1}^p \left(\frac{1}{|C_l|} \sum_{i, i' \in C_l} x_{ij}^2 - 2 \frac{1}{|C_l|} \sum_{i, i' \in C_l} x_{ij}x_{i'j} + \frac{1}{|C_l|} \sum_{i, i' \in C_l} x_{i'j}^2 \right) \\ &\stackrel{(\text{Remark 3.2})}{=} \sum_{j=1}^p \left(\sum_{i \in C_l} x_{ij}^2 - 2\bar{x}_{lj} \sum_{i \in C_l} x_{ij} + \sum_{i' \in C_l} x_{i'j}^2 \right) \\ &\stackrel{(\text{Remark 3.2})}{=} 2 \sum_{j=1}^p \left(\sum_{i \in C_l} x_{ij}^2 - |C_l| \bar{x}_{lj}^2 \right) \\ &\stackrel{(\text{Remark 3.3})}{=} 2 \sum_{i \in C_l} \sum_{j=1}^p (x_{ij} - \bar{x}_{lj})^2 \end{aligned}$$

□

The approach of k -means is to find a partitioning of the data set in such a way that the sum of the variations is minimized.

Definition 3.4 (k -means). Let $X = \{x_1, \dots, x_n\}$ be a data set and $\{C_1, \dots, C_k\}$ a partition. Then k -means tries to find an optimal partition $C^* = \{C_1^*, \dots, C_k^*\}$ such that:

$$\sum_{l=1}^k D(C_l^*) = \min_{C_1, \dots, C_k} \sum_{l=1}^k D(C_l) = \min_{C_1, \dots, C_k} 2 \sum_{l=1}^k \sum_{i \in C_l} \sum_{j=1}^p (x_{ij} - \bar{x}_{lj})^2 \quad (3.2)$$

3. *k*-means

When it comes to solving the optimization problem defined by formula (3.2), the computational complexity of the algorithm to be used is of high interest. Therefore computational complexity theory categorizes problems into different classes that have some defining properties, one of which is called NP-hard. The definition of these classes would go beyond the scope of this work and therefore only a reference to the literature is given here e.g. [np'hard'reference]. In very simplified terms one can say that there are currently no efficient algorithms for this type of problem.

Corollary 3.2. *Solving the *k*-means problem defined in (3.2) is NP-hard.*

Proof. c.f. [NP'hard]

□

Even though the problem is NP-hard it is still possible to provide algorithms which converge to a local optimum. The algorithms used for finding a local minimum work on an iterative basis and involve just a few different steps. The *k*-means algorithms either start with an initial assignment of all observations to *k* different clusters or with *k* distinctly selected cluster centers. The next step is to find a new cluster center such that the variation $D(C_l)$ is minimized within each cluster. Then all data points $X = \{x_1, \dots, x_n\}$ are reassigned to the cluster which is nearest and the minimization procedure is repeated until convergence.

Remark 3.4.

(i) For $k = n$, (3.2) is zero because each data point represents a cluster.

One possible formulation for an algorithm that converges to a local optimum is the one from Lloyd [lloyd1982least] which a pseudo code is given below. Note that for algorithm 2 we have a fixed number of clusters *k* as well as a finite set of possible partitions k^n . We can therefore show that the stated algorithm converges to a local minimum by minimizing (3.1).

Remark 3.5.

(i) For any set of observations *S* it holds that:

$$\bar{x}_S = \underset{x}{\operatorname{argmin}} \sum_{i \in S} (x_i - x)^2$$

Hence, step 2a) minimizes the sum of squared deviations and therefore $D(C_l)$.

- (ii) Step 2b) which reassigns the observations to the new nearest centroid can only reduce the objective function.

Algorithm 2 k -means clustering [Introduction Stat Learning] - Lloyd's algorithm

1. Choose k initial centroids randomly.
 2. Iterate till the cluster assignments stop changing:
 - a) For each of the k clusters, compute the cluster centroid. The i -th cluster centroid is the vector of the p parameter means for the observations in the i th cluster.
 - b) Assign each observation to the cluster whose centroid is closest in the sense of Euclidean distance.
-

Remark 3.6.

- (i) The k -means algorithm always converges and finds a local optimum which need not to be the global one.
- (ii) Different clustering results can be obtained when different initial cluster assignments in step 1 of algorithm 2 are chosen.

Remark 3.7 (Running Time).

- (i) Algorithm 2 has a running time of $O(nkpi)$, with n being the number of data points, k the number of cluster, p the number of dimensions and i the number of iterations needed to converge. The only unknown variable is the number of iterations.
- (ii) The trivial upper bound for the number of iterations needed is given by $O(k^n)$, because the algorithm visits every partition of points only once.
- (iii) It can be shown [arthur2006slow] that in the worst case scenario the running time of the algorithm is superpolynomial with a lower bound for the number of iterations of $O(2^{\Omega(\sqrt{n})})$. That means that the running time cannot be bounded above by any polynomial function.
- (iv) In practice, the number of iterations required is often small, which makes the algorithm appear to be linearly complex.

It is advisable to run the algorithm several times with different initial centroid assignments. This increases the likelihood of finding a partition that is

3. *k*-means

close to the optimum and thus provides a low value for the objective function (3.2). However, the biggest challenge when using *k*-means is the estimation of the optimal number of clusters k . Figure (3.1) shows an example with three clusters that illustrates the different clustering results when the number of k increases. Panel (a) shows the raw data with three clusters ($k_{true} = 3$), each generated by an uniform distribution. Panels (b), (c) and (d) show the cluster results with $k = 2, 3$ and 7 , respectively. If the number of clusters k is smaller than the actual number of clusters in the data, then *k*-means merges clusters, while for k greater than k_{true} , *k*-means divides well separated clusters. Panel (b) shows a merge of the clusters at the top right, whereas panel (d) shows an artificial split of two natural clusters for $k = 5$. For the grouping of similar data points and their representation by a cluster center, an underestimation of the actual number of clusters is more critical than an overestimation. If k underestimates the true value of clusters ($k < k_{true}$), then it's not possible to capture the cluster specific characteristics for the merged clusters because they are represented by only one cluster center. However, an overestimation of k_{true} is not so critical because some natural clusters will be represented by two cluster centers which has a negative impact on the compression ratio but not the clustering quality. For the most crucial step of *k*-means, a comprehensive collection of methods for estimating the correct number of clusters can be found in [milligan1985examination]. In the following, the ‘elbow’ and silhouette method, two widely used graphical methods for estimating k_{true} , are presented and applied to the sample data set.



Figure 3.1.: Results for a three-cluster example: (a) raw data; (b) $k = 2$; (c) $k = 3$; (d) $k = 5$

3.1. Elbow method - gap statistic

Estimating k , the parameter that defines the number of clusters, is one of the most difficult tasks when using k -means. While it is still possible to graphically determine the number of clusters by plotting the data in 2 or 3 dimensional spaces, other methods must be used in higher dimensions. The ‘elbow’ method is one of the most commonly used methods in this context.

Definition 3.5. *Let $X = \{x_1, \dots, x_n\}$ be a data set and k the number of clusters. Then $C = \{C_1, \dots, C_k\}$ is the corresponding partition with the sum of variation within all clusters defined as:*

$$V_k := \sum_{r=1}^k \frac{D(C_r)}{2}$$

Plotting V_k , the sum of variation within all clusters as a measure of total error versus the number of clusters used gives a good indication for the true value of k . Figure 3.2(a) shows that the error measure V_k decreases monotonically as the number of clusters increases but there seems to exist a k from which the decline is clearly flattened. Such an ‘elbow’ indicates that any additional cluster reduces the total variation V_k only slightly and an appropriate number of clusters can be derived from the location of the ‘elbow’. In accordance with $k_{true} = 3$, the ‘elbow’ plotted in 3.2(a) indicates that the true number of clusters is three, because there the curve starts to flatten dramatically. Even if the sample data set consists of very well separated clusters, the example indicates that the method could also be suitable in general use cases. For a small number of tasks the graphical determination of the “elbow” is practicable, but an automated method is needed with an increasing number of clustering operations. A statistical method that formalizes this procedure of finding the ‘elbow’ is described in [tibshirani2001estimating]. The basic idea is to make the sum of variation V_k comparable to a reference. For this purpose, the sum of deviations is calculated for each k and then compared with the expected sum of the deviations derived from a reference data set with no obvious clustering. The reference data set is generated by sampling uniformly over the range of the observed values for every feature from the original data set. This means it is sampled uniformly from the smallest p -dimensional cube that contains all data points $\{x_1, \dots, x_n\}$ of the original data set.

Definition 3.6. *Let k be the number of clusters and \mathbb{E}_n the expectation under a sample of size n from the reference distribution. Then the gap-statistic is*

3.1. Elbow method - gap statistic

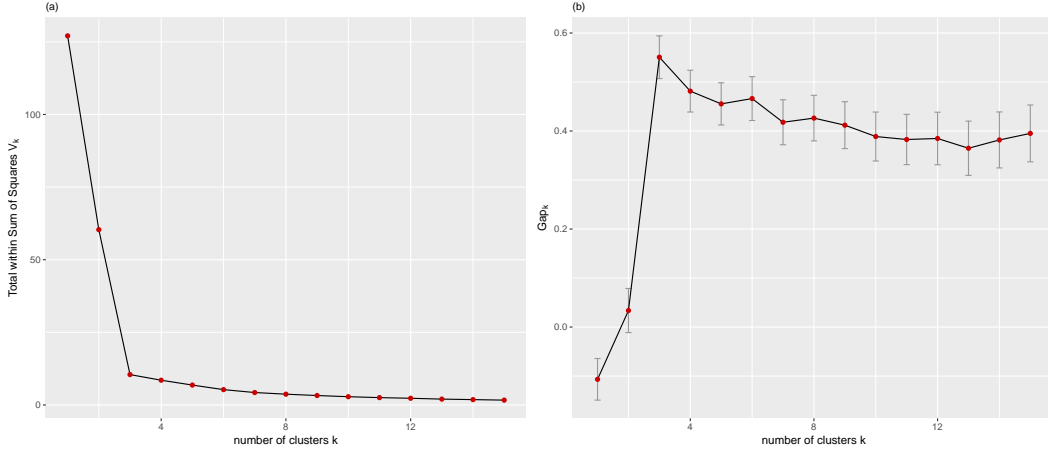


Figure 3.2.: Three-cluster example: (a) Total within Sum of Squares; (b) Gap-Statistic

defined as:

$$Gap_n(k) := \mathbb{E}_n[\log(V_k)] - \log(V_k) \quad (3.3)$$

To determine the expected value $\mathbb{E}_n[\log(V_k)]$ we draw B different samples $\{x_1^*, \dots, x_n^*\}$ from the p -dimensional cube and average over the B values of $\log(V_k)$. Accounting for the simulation error introduced by using the B Monte Carlo samples the standard deviation is given by:

$$s_k = \sqrt{1 + \frac{1}{B}} sd(k)$$

The optimal cluster size k is then determined by the following rule which identifies the ‘elbow’:

Definition 3.7. Let $Gap(k)$ be the statistic defined above and s_k the standard error (c.f. [tibshirani2001estimating]). Then the rule for choosing k is given by:

$$\hat{k} := \text{smallest } k \text{ such that } Gap(k) \geq Gap(k+1) - s_{k+1} \quad (3.4)$$

In order to find the optimal number of clusters in a computational way, the following steps described in algorithm 3 are necessary:

Figure (3.2)(b) shows the gap-statistic for different values of k with the corresponding standard errors as a vertical bar. The application of the proposed rule

3. k -means

Algorithm 3 Ellbow method [tibshirani2001estimating]

1. Define the maximal number of clusters k_{max}
2. Iterate over $k = 1, \dots, k_{max}$:
 - a) Apply the k -means algorithm to the data set $\{x_1, \dots, x_n\}$ and calculate $\log(V_k)$.
 - b) Generate B reference data sets, each of them having n samples $\{x_1^*, \dots, x_n^*\}$.
 - c) Cluster each of those B data sets and calculate $\mathbb{E}_n[\log(V_k)] = \frac{1}{B} \sum_{b=1}^B \log(V_{kb})$
 - d) Compute the standard deviation:

$$sd(k) = \left(\frac{1}{B} \sum_{b=1}^B (\log(V_{kb}) - \mathbb{E}_n[\log(V_k)])^2 \right)^{\frac{1}{2}}$$

- e) End the loop if: $Gap(k) \geq Gap(k+1) - s_{k+1}$
-

(3.4) for selecting the number of clusters results in $\hat{k} = 3$ which corresponds exactly to the actual number of clusters in the data set.

3.2. Silhouette method

Although the "elbow method" is well suited in many cases to determine the number of clusters, the resulting partitioning is not visually displayable if the dimension is larger than three. A visually appealing graphical display called silhouette plot introduced in [rousseeuw1987silhouettes] tries to overcome this shortcoming in order to be able to interpret cluster results more properly. The plot shows whether a specific partitioning result reflects a cluster structure actually present in the data set or not, by comparing the within dissimilarity with the between dissimilarity for every data point. It can thus be determined how similar a data point is to its own cluster compared to the other clusters. The measure of similarity can be calculated with any distance metric appropriate to the specific problem and will be called $dist(x_i, x_j)$ for two data points x_i and x_j .

Definition 3.8 (Within dissimilarity). *Let $X = \{x_1, \dots, x_n\}$ be a data set and $C = \{C_1, \dots, C_k\}$ the corresponding partitioning with k cluster. Assume that*

3.2. Silhouette method

the data point x_i is assigned to cluster C_i with $1 \leq i \leq k$. Then the average dissimilarity of x_i to all other objects assigned to cluster C_i is defined by:

$$WD(C_i, i) := \frac{1}{|C_i|} \sum_{x_l \in C_i} \text{dist}(x_i, x_l)$$

One can think of $WD(C_i, i)$ as a measure of how well the data point x_i is embedded in its cluster C_i . The smaller the value, the closer the data points of the cluster are to each other on average.

Definition 3.9 (Between dissimilarity). *Let $X = \{x_1, \dots, x_n\}$ be a data set and $C = \{C_1, \dots, C_k\}$ the corresponding partitioning with k cluster. For any cluster C_j different from C_i (i.e. $i \neq j$) the average dissimilarity of $x_i \in C_i$ to the cluster C_j is given by:*

$$BD(C_j, i) := \frac{1}{|C_j|} \sum_{x_l \in C_j} \text{dist}(x_i, x_l)$$

One can see that $BD(C_j, i)$ is the average distance from data point x_i in cluster C_i to all data points x_j in cluster C_j .

Definition 3.10. *Let $X = \{x_1, \dots, x_n\}$ be a data set and $C = \{C_1, \dots, C_k\}$ the corresponding partitioning with k cluster. For any data point x_i assigned to cluster C_i (e.i. $x_i \in C_i$) the distance to the closest neighbor cluster is given by:*

$$\text{dist}(i) := \min_{C_i \neq C_j} BD(C_j, i)$$

Cluster C_b with $1 \leq b \leq k$, which shares the smallest average dissimilarity with point $x_i \in C_i$ is called the neighbor cluster of x_i . This neighbor cluster is the first choice if cluster C_i is removed from our analysis and we have to reassign x_i to a new cluster. After computing $WD(C_i, i)$ and $\text{dist}(i)$ for every data point x_i , $i = 1, \dots, n$ one can define the silhouette statistic $s(i)$ as follows.

Definition 3.11. *Let $X = \{x_1, \dots, x_n\}$ be a data set and $C = \{C_1, \dots, C_k\}$ the corresponding partitioning with k cluster. For every $x_i \in X$ the silhouette $s(i)$ is defined as:*

$$s(i) = \begin{cases} 1 - \frac{WD(C_i, i)}{\text{dist}(i)} & \text{if } WD(C_i, i) < \text{dist}(i) \\ 0 & \text{if } WD(C_i, i) = \text{dist}(i) \\ \frac{\text{dist}(i)}{WD(C_i, i)} - 1 & \text{if } WD(C_i, i) > \text{dist}(i) \end{cases}$$

3. k -means

Remark 3.8. We can write the silhouette $s(i)$ in a more compact form:

$$s(i) = \frac{\text{dist}(i) - WD(C_i, i)}{\max\{WD(C_i, i), \text{dist}(i)\}}, \quad \text{if } |C_i| > 1$$

$$s(i) = 0 \quad \text{if } |C_i| = 1$$

Remark 3.9. For every x_i it is true that $-1 \leq s(i) \leq 1$.

Remark 3.10. In order to understand which values of $s(i)$ correspond to which clustering results, it makes sense to look at values at the boundaries:

- ★ $s(i) \in (1 - \epsilon, 1]$: For $s(i)$ close to 1 the within dissimilarity of x_i is much smaller than the minimum between dissimilarity. This shows on the one hand that the data point x_i is very well embedded in its cluster and has a small distance to the other data points of its cluster (i.e. $WD(C_i, i)$ small). On the other hand a relatively large value of $\text{dist}(i)$ shows that the minimum distance from x_i to the nearest cluster is very large. Thus one can speak of adequate clustering.
- ★ $s(i) \in (-\epsilon, +\epsilon)$: The within dissimilarity of x_i is approximately the same as the minimum between dissimilarity which indicates that x_i lies between two cluster. A small change of the data point x_i could cause it to be assigned to another cluster, suggesting unstable results.
- ★ $s(i) \in [-1, -1 + \epsilon)$ The minimum between dissimilarity of x_i is much smaller than the within dissimilarity which indicates that x_i may not be correctly clustered. In this case x_i is on average much closer to the neighbor cluster than to the actual cluster which rises doubts if the cluster assignment is right.

Remark 3.11. Let x_i be a data point which is assigned to cluster C_i and cluster C_j the neighbor cluster of x_i . If x_i is reassigned from cluster C_i to cluster C_j then $s(i)$ becomes $-s(i)$

In order to get a visually appealing overview if a clustering result is good or not all silhouettes are plotted on top of each other. Silhouettes which belong to the same cluster are plotted together and ranked in decreasing order.

Figure (3.3) shows the silhouette plot for the sample data set with $k = 3$ and 5, respectively. Each silhouette plots shows on the right side the cluster name, the number of data points assigned to the cluster and the average silhouette width. In the right panel of figure (3.3) cluster 1 consists of 11 data points

3.2. Silhouette method

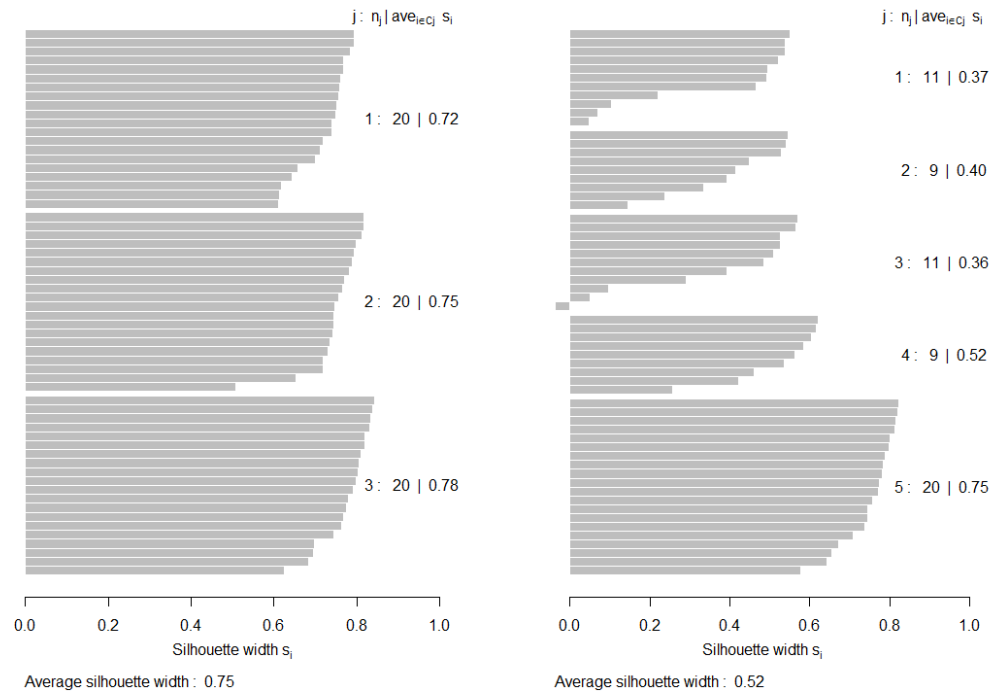


Figure 3.3.: Left: silhouette plot for $k = 3$; Right: silhouette plot for $k = 5$

3. k -means

and has a average silhouette width of 0.37. In cluster 3, for example, two data points have a silhouette width $s(i)$ close to zero and one data point has a negative value for $s(i)$. Except for cluster 5, all other clusters include data points which have a small or even negative value for $s(i)$. At the bottom of each silhouette plot the average silhouette width for all data points is given. The silhouette plot with $k = 3$ has much wider silhouettes compared to the plot with $k = 5$ which is an indicator that only 3 clusters are present in the data. Similar plots for $k = 2$ and $k = 4$ also lead to the conclusion that the data consists of 3 natural clusters. If there are too many ($k > k_{true}$) or too few clusters ($k < k_{true}$) some of the cluster silhouettes will be much narrower compared to the others.

Remark 3.12. *A high average cluster silhouette width indicates that the cluster is well separated from other clusters and is not split up artificially.*

Remark 3.13. *It can be seen that artificial splits of clusters gets quite heavily penalizes by the silhouette coefficient. The average silhouette width drops from 0.75 to 0.52 if the number of cluster is increased from $k = 3$ to $k = 5$ as seen in figure (3.3).*

3.3. Curse of dimensionality

After presenting two methods namely the elbow method and silhouette method which help identifying the correct number of clusters one should also be aware of phenomena that arise when analyzing data in high dimensional spaces. The ‘curse of dimensionality’ is a term introduced by Richard Bellman [bellman1961adaptive] to describe the rapid increase in volume and therefore the intractability of algorithms, when adding more dimensions of data to a mathematical space. Nowadays there are many different phenomenons referred to when talking about the curse of dimensionality but in the subsequent the focus is on distance functions as a measure of similarity. So far, all the methods presented are based extensively on the underlying distance functions used. To get a better understanding on the issue a simple example is given that helps to illustrate the problem.

Example 3.2.

- (i) *Imagine a line segment of length 1, and 10 data points which should represent the line. To capture the whole line segment one would distribute the points uniformly across the line. Therefore the line would be divided*

3.3. Curse of dimensionality

into 10 segments with length $\frac{1}{10}$ and the points are centered within these segments.

(ii) By adding one dimension the line segment becomes a square segment with edge length 1. In order to represent the ‘same’ space with a data point as in the one-dimensional case, the square would have to be divided into 100 smaller squares with an edge length of $\frac{1}{10}$ each. In the center of each of those square segments one data point is needed as a representative. A total of 100 data points are required to represent the square segment as exactly as the line segment.

(iii) By adding another dimension the square segment becomes a cube and 1000 points are needed.

Example 3.2 illustrates that as the number of dimensions increases the number of data points rises exponentially in order to represent the whole space properly. Thinking of insurance data, one can have data points with various numbers of dimensions ranging from just a few to several hundreds dimensions. Considering the fact that the cash flow projections of grouped policies should coincide over a 60 year horizon, it is easy to see that only 5 of these cash flow characteristics (e.g. premium, costs, ...) result in data points with a dimension of 300. Of course, it is not advisable to include, over a period of 60 years, all cash flow variables in the grouping process, but it is much more difficult to find only those variables that are relevant for a major part of the results than including everything. For this reason, in practice more variables are often used than would actually be necessary. Another unintuitive fact one needs to be aware of is that the volume of a hypersphere inscribed into a hypercube is getting relatively smaller as the dimension increases.

Corollary 3.3. *Let a hypersphere with radius r and dimension d be inscribed into a hypercube with edges of length $2r$. Then we get for the proportion of the volumes:*

$$\frac{V_{Sphere}}{V_{Cube}} = \frac{r^d \frac{\pi^{\frac{d}{2}}}{\Gamma(\frac{d}{2}+1)}}{(2r)^d} = \frac{\pi^{\frac{d}{2}}}{2^d \Gamma(\frac{d}{2}+1)} \rightarrow 0 \text{ as } d \rightarrow \infty$$

Remark 3.14. *Corollary 3.3 says that as dimension d increases, more and more volume of the hypercube is outside the hypersphere. This means that under a uniform distribution most of the data points are located far from the center and thus close to an edge in a certain sense.*

Remark 3.15. *Some other examples why intuition fails in high dimensions are given in paragraph 6 of [domingos2012few].*

3. *k*-means

Not only do the data points move closer to the edge as the dimension d of the data space increases, but the distance between the individual data points is becoming more and more similar. It can be shown ([beyer1999nearest]) that under a broad set of conditions the distance to the nearest and to the farthest data point converges as dimensionality d increases. Experimental results in [beyer1999nearest] show that this effect can occur even for relatively low dimensional data with only 10 to 15 dimension. The fact that the distance to the farthest data point can get similar to the distance of the nearest data point makes clustering a hard job. The basic concept of *k*-means is to find, in the case of the Euclidean distance measure, spherically shaped clusters that have different characteristics. Therefore, data that is almost identical should not be clustered with a simple *k*-means algorithm without further analysis. Due to the fact that the *k*-means algorithm always returns a result even though there are obviously no clusters in the data because all data points are somehow similar, it is very difficult to determine whether *k*-means is a suitable tool for clustering or not. Situations in which all data points are similar and no cluster structure is present in the data are, as shown in the previous section, indicated by a low silhouette coefficient. When using the methods described in section 3.2, a silhouette plot with low silhouette coefficients for the clusters indicates that the clusters found by the algorithm are not well separated. Single clustering attempts can easily be verified by an visual inspection of plots described above. With an automated clustering approach, which is necessary for large insurance portfolios, visual control of the individual silhouette plots is not possible in most cases. In such cases, only a validation of the silhouette coefficient is feasible, but this leads ultimately to a situation where a clustering result is validated by a single value. It is therefore advisable to use low-dimensional policy data sets or conduct a thorough analysis of the data to avoid situations where problems referred to as 'curse of dimensionality' occur.

4. Non-negative least squares (NNLS)

Another way to find a grouped portfolio that minimizes the deviation defined in formula (1.1) is to solve the problem using mathematical optimization methods. The goal is to find a subset of the portfolio and scale it in way so that the square deviation becomes minimal. Of course, this approach must ensure that scaling is only possible in the positive direction. This means that it makes no sense to have a negative policy in the grouped portfolio, because it cannot be defined, not to mention explained logically.

Definition 4.1 (Non-negative least squares). *Let $P \subset \mathcal{V}$ be a portfolio, $A \in \mathbb{R}^{m \times n}$ the matrix with the corresponding cashflows and $b \in \mathbb{R}^m$ the vector with the summed cashflows. Then $x \in \mathbb{R}^n$, the vector of scaling, should be optimized such that:*

$$\begin{aligned} \arg \min_x & \|Ax - b\|_2^2 \\ & \text{subject to } x \geq 0 \end{aligned} \tag{4.1}$$

Remark 4.1.

- *The entries of the vector x are the so-called scaling values for the cashflows in matrix A . Each entry $x_i, i \in \{1, \dots, n\}$ that is greater than zero scales to the i -th column of matrix A where column i represents the cashflows of the i -th policy of the portfolio.*
- *It should be noted that this approach optimizes cashflows, not policies. Since there is a one-to-one relationship between cashflows and policies, the scaling factors cannot only be used to scale the cashflows but also to scale the policies in order to create a grouped portfolio.*
- *Scaling policies can also involve risks, as a policy that is scaled by a factor of 2 will not necessarily produce cash flows that are also increased by a factor of 2. This can be attributed to the fact that, for example, non-linearities occur due to discount effects for higher premiums in the tariff.*

4. Non-negative least squares (NNLS)

Remark 4.2. *The number of policies in the grouped portfolio corresponds exactly to the number of entries greater than zero in the vector x .*

One of the well known algorithms for solving the non-negative least square problem is that of Lawson and Hanson, which uses an active set method. The steps necessary for solving that problem are given in [lawson]. Additionally to those parameters defined in definition 4.1 one also needs a real value variable ϵ as a stopping criterion.

Algorithm 4 Non-negative least squares [lawson]

1. Set $P = \emptyset$, $R = \{1, \dots, n\}$, $x = 0_{n \times 1}$
 2. Compute $w = A^\top(b - Ax)$.
 3. While $R \neq \emptyset$ and $\max(w) > \epsilon$
 - a) Find index $j \in R$ such that $w_j = \max\{w_t, t \in R\}$.
 - b) Move the index j from R to P .
 - c) Let A^P be A restricted to the variables included in P .
 - d) Let s be a vector of same length as x . Let s^P denote the sub-vector with indexes from P , and let s^R denote the sub-vector with indexes from R .
 - e) Compute $s^P = ((A^P)^\top A^P)^{-1}(A^P)^\top b$
 - f) Set $s^R = 0$.
 - g) While $\min(s^P) \leq 0$
 - i. Set $\alpha_k = \min \frac{x_i}{x_i - s_i}$ for i in P where $s_i \leq 0$
 - ii. Set $x = x + \alpha_k(s - x)$
 - iii. Move from P to R all indices $k \in P$ for which $x_k = 0$.
 - iv. Compute $s^P = ((A^P)^\top A^P)^{-1}(A^P)^\top b$
 - v. Set $s^R = 0$
 - h) Set x to s
 - i) Compute $w = A^\top(b - Ax)$.
-

Algorithm 4 consists, apart from the initialization, of a main loop and an inner loop. The loops are highlighted by indentations and start at step 3 and step g) respectively. If for a variable reference is made to those indices of the variable which are contained in the set R , then these entries are 0. All indexes that exist in the set P , by contrast, have nonzero values. If such a variable has a negative value, the algorithm either moves it to the positive value range or sets

it to zero. By setting a variable to zero, the index is also shifted from the set P to the set R . This ensures that the following condition is met at the end of the algorithm.

$$\begin{aligned} x_j &> 0, & j &\in P \\ x_j &= 0, & j &\in R \end{aligned} \tag{4.2}$$

Remark 4.3. Let $f(x) = \|Ax - b\|_2^2$ be the function, then the gradient is given by:

$$\nabla f(x) = \nabla \|Ax - b\|_2^2 = A^\top (Ax - b)$$

$$\begin{aligned} \nabla \|Ax - b\|_2^2 &= \nabla (Ax - b)^\top (Ax - b) \\ &= \nabla (x^\top A^\top - b^\top) (Ax - b) \\ &= \nabla (x^\top A^\top Ax - x^\top A^\top b - b^\top Ax + b^\top b) \\ &= \nabla (x^\top A^\top Ax - 2x^\top A^\top b + b^\top b) \\ &= 2(A^\top Ax - A^\top b) \\ &= 2A^\top (Ax - b) \end{aligned}$$

As shown in remark 4.3, step 2 of algorithm 4 calculates the negative gradient of the ordinary least squares problem. In the next step it is checked whether the inner loop still has to be executed or not. If the index set R correspond to the empty set then all indexes are already in P which means that all entries of x are positive (see formula (4.2)). This case is not desirable, as no compression can be achieved. If $\max(w) \leq \epsilon$ is satisfied, the gradient has no entry large enough, so that an substantial improvement can be achieved and the algorithm has reached the optimum. If one of the two conditions in step 3) is fulfilled, the main loop is executed.

The main loop starts with searching for the index of the gradient that is not yet present in the set P and has the highest value. After this index has been moved from the set R to the set P , the solution of a restricted least square problem is calculated in step e). This least squares problem is limited to the columns of the matrix A whose indices occur in the set P . The result is then a vector of dimension P which is indicated by the notation s^P . To get a solution vector of the dimension n , the $n - |P| = |R|$ entries s^R of the vector s are filled with 0 - see step f).

4. Non-negative least squares (NNLS)

Example 4.1. Based on algorithm 4, be $n = 15$, $P = \{2, 3, 4, 5, 7, 9\}$ and $R = P^c = \{1, 6, 8, 10, 11, 12, 13, 14, 15\}$ then

$$s = \begin{pmatrix} s_1 \\ s_2 \\ \vdots \\ s_{15} \end{pmatrix} \quad s^P = \begin{pmatrix} s_2 \\ s_3 \\ s_4 \\ s_5 \\ s_7 \\ s_9 \end{pmatrix} \quad s^R = \begin{pmatrix} s_1 \\ s_6 \\ s_8 \\ s_{10} \\ \vdots \\ s_{15} \end{pmatrix}$$

If all components of this least square solution (i.e. s^P) are positive a new solution has been found and the solution vector x is overwritten with s as seen in step h). In step i) a recalculation of the gradient with the solution x , adapted in the previous step, is carried out and the main loop is restarted by checking the conditions in step 3.

If there are non positive entries in the solution of the restricted least squares problem computed in step e), the inner loop is executed. Basically, negative entries in the result vector s^P would lead to a new solution vector x which would also have negative entries without further adjustments, resulting in an undesired solution since x must be non-negative (i.e $x \geq 0$). Therefore, based on the current solution vector x which has only positive entries, a shift is carried out by using s^P . In the first step the index $k \in P$ is determined which leads to the smallest scaling factor α_k . The current solution vector x is then shifted by using this factor which causes the entry x_k to be zero after the shift. The index k can thus be moved from set P back to set R because the corresponding entry x_k is zero after the shift. In the unlikely event that several entries of the new solution vector x were changed to zero as a result of the shift, all these indexes must of course be moved from set P to set R (see iii.). Based on the new set P , a new limited least squares problem will be solved and the inner loop will be redone if necessary.

Remark 4.4. Since $x_i \geq 0$ at all times and $s_j \leq 0$ within the inner loop, the scaling factor is bounded by $0 \leq \alpha_k \leq 1$.

Remark 4.5. Within the inner loop, at least one index k per iteration is transferred from the set P to the set R . As a result, with each pass of the inner loop, the number of entries in the solution vector x that are not equal to zero is reduced by at least one. Since the cardinality of the set P is finite, it is also determined how often the inner loop is run through at the most, namely $|P| - 1$ times.

As stated in [lawson], for many examples the steps of the outer loop are simply repeated by adding another positive coefficient to the solution vector x until one of the termination criteria in step 3 are fulfilled. This observation may be correct for many different application areas, but must be verified with respect to the policy data being optimized. For this purpose, a standard portfolio of policies is used in which the development of the vector x is analyzed. The test portfolio consists of 20.000 randomly selected policies using 351 cash flows for each policy.

Figure (4.1) shows how the number of non-negative entries of the solution vector x evolves. After the algorithm is started with an initialization, the solution vector x only has entries that are zero and the next step is to execute the main loop for the first time. So the graph starts in (0,0). After passing through the main loop for the first time, the first entry of x became a positive value and the graph displays this as the point (1,1). Also the next 9 passes of the main loop run exactly as just described so that after 10 iterations 10 entries of x are not equal to zero and the graph is at (10,10). In the next pass of the main loop, the solution s^P , see step e), of the restricted least squares problem becomes for the first time not positive for at least one entry and the inner loop is executed. When entering the inner loop, s^P has the dimension 11. Within the inner loop, as explained above, a shift is performed and the index k is shifted from the set P to the set R . Due to this shift of the index and the subsequent recalculation of the now dimensionally reduced least squares problem (see iv.), s^P now has only dimension 10. Since none of these 10 entries is not positive, the inner loop is now left. The solution vector still has only 10 positive entries after the 11 iteration and therefore the point (11,10) results. The just described phenomenon that the inner loop is left again after one iteration, since all negative entries have been removed, can be observed in figure (4.1) more often. This is exactly the case when a horizontal line is present. In the above example, it is also easy to see that this phenomenon of horizontal lines occurs more frequently after about 50 iterations. This can be explained by the fact that at the beginning of an optimization the limited least square problem which need to be solved has a small dimension and therefore it is less likely to get negative solution values. In the progress of the optimization, the achievable improvements of the objective function become smaller and smaller on also the cardinality of the set P increases. The last feature in figure (4.1) that can be observed is that of a descending line. This case occurs for the first time at the transition from iteration 28 to iteration 29. In iteration 29 the solution vector of the limited least square problem s^P has entries that are not positive such as in the case described previously. The difference to

4. Non-negative least squares (NNLS)



Figure 4.1.: Development of the non-negative entries of the solution vector x based on the number of iterations.

before is that the inner loop is not left after one iteration. So there are several loop cycles required to adapt all negative entries by shifting. In the particular case of iteration 29, the inner loop is executed exactly twice until all entries of s^P are positive. Since with each pass of the inner loop the number of positive entries of the solution vector x is reduced by one, a descending line results after 2 passes. It is therefore clear that the steepness of the descent is a measure of how often the inner loop has been looped before all entries were positive.

If not the number of non-negative entries is considered but the development of 4.1 for each iteration, a similar picture emerges. Graph (4.2) shows the logarithmic sum of the squared deviations between the fitted cashflows Ax and the reference cashflows b . The graph is monotonously falling and can be compared in its characteristics with the previous figure (4.1). Starting with the initialization, the solution vector x has only zero entries and therefore $\|Ax - b\|_2^2$ reduces to $\|b\|_2^2$ which gives the first data point of the graph at $(0, 2.13e+20)$. Especially at the beginning of the optimization, a new non-



Figure 4.2.: Development of the deviance based on the number of iterations.

negative entry in x is added with each iteration, as seen in figure (4.1). This is also reflected in the fact that in figure (4.2) the deviation falls significantly for the first iteration. From iteration 50 on there is a clear flattening of the curve which indicates that from then on the improvements of the target function are no longer possible to the same extent as at the beginning of the optimization. This is also confirmed by the fact that after 25% of the iterations 99.9% of the reduction of the target function has already taken place. The remaining 0.1% improvement to the final optimized value of problem (4.1) then take place in the last 75% of the iterations. Since, as described in more detail in the next section, the inversion of matrices is one of the most time-consuming steps in terms of execution time, it can be useful to cancel an optimization prematurely. A large part of the computing time could be saved and at the same time only a fraction of the optimization quality would be lost.

4. Non-negative least squares (NNLS)

4.1. Numerical Aspects

As evident in figure (4.1) as well as figure (4.2), the optimization is stopped after 214 iterations. The reason for this is neither that a sufficiently large gradient is no longer available nor that the set R is empty. So all conditions of the main loop stated in step 3 of algorithm 4 are still fulfilled. Rather, a stable state has occurred which does not allow any further improvement of the results. Reaching a stable state during an optimization is one of several reasons for an optimization to stop.

Facing a stable state involves a very special case of index shifts between the sets R and P , which must be handled separately by the algorithm. Starting from a gradient calculated in step i), the new index j in R is searched for which has the maximum gradient. This new index is then moved from the set R to the set P and the constrained least squares problem is calculated as specified in step e). Since the vector s^P now has exactly one negative entry, the inner loop must be entered in the next step. It turns out that exactly that index j of s is negative which was added by the shift from j to P in the last main loop. Since the corresponding entry x_j is zero and s has only one negative entry, the scaling factor α also has a value of zero. This leads to the fact that the shift specified in step ii. has no effect and the solution vector x remains the same. In step iii. the previously determined index j will then be shifted back from the set P to the set R . In the next iteration of the main loop, the index with the largest gradient is found again as the previously moved index j . This will lead to what has just been described, resulting in an infinite loop. A case such as this therefore only occurs if the following two conditions occur simultaneously:

1. The solution vector s^P of the constrained least squares problem has one negative entry.
2. This negative entry is in vector s exactly at the index that was transferred from set R to set P in the current loop pass in step b).

Remark 4.6. *If the stopping reason of the optimization algorithm is the reaching of a stable status, the number of non-negative entries of the solution vector x must be equal for the last two iterations. This means that in figure (4.1) the graph has to end with a horizontal line.*

Another reason that can lead to an unplanned termination of the optimization algorithm is related to solving process of the restricted least squares problem

in step e) and iv). In these steps the solution of the constrained least squares problem is calculated which requires the use of an inverse matrix. If the inverse of $((A^P)^\top A^P)^{-1}$ does not exist, an alternative solution has to be found. The most practicable approach is to test whether an inverse exists using the determinant of $(A^P)^\top A^P$. If this is not the case, remove the just added index j from the set P and replace it with a j' which has the second largest gradient. Not only the existence of the inverse matrix is important but also its numerical stability. Therefore it should be ensured that with a small change of the matrix A , the inverse matrix A^{-1} do not change significantly in order to get stable results. To determine whether the inversion of a matrix A is numerically stable, a new concept must be introduced which characterizes the numerical stability.

Definition 4.2. *Let V and W be normed vector spaces and $f : V \rightarrow W$ a linear operator. Then the operator norm is given by:*

$$\|f\| := \sup_{x \in V \setminus \{0\}} \frac{\|f(x)\|_W}{\|x\|_V} = \sup_{\|x\|_V=1} \|f(x)\|_W \quad (4.3)$$

Remark 4.7. *Since every real valued matrix $A \in \mathbb{R}^{m \times n}$ corresponds to a linear map from \mathbb{R}^n to \mathbb{R}^m , each pair of norms induces an operator norm. In the special case of choosing the Euclidean norm for both vector spaces, (4.3) simplifies to:*

$$\|A\|_2 := \max_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2} = \max_{\|x\|_2=1} \|Ax\|_2 \quad (4.4)$$

which is a naturally induced matrix norm called spectral norm.

The natural matrix norm thus vividly corresponds to the greatest possible stretching factor, which results from the application of the linear mapping (i.e. matrix) to a unit vector.

Remark 4.8. *The naturally induced matrix norm satisfies the three norm axioms:*

- $\|A\| = 0$ iff $A = 0$ (being definite)
- $\|\alpha A\| = |\alpha| \|A\|$ (being absolutely homogeneous)
- $\|A + B\| \leq \|A\| + \|B\|$ (being sub-additive)

Remark 4.9 ([stewart1998matrix]). *The 2-norm has the following properties:*

4. Non-negative least squares (NNLS)

1. $\|A\|_2 = \sigma_{\max}(A)$ *largest singular value of A*
2. $\|A\|_2^2 = \lambda_{\max}(A^T A)$ *largest eigenvalue value of $A^T A$*
3. $\|A\|_2 = \|A^T\|_2$

Definition 4.3. Let $A \in \mathbb{R}^{m \times n}$ be a matrix and $\|\cdot\|$ a matrix norm. Then the condition number of A is defined as:

$$\kappa(A) := \|A^+\| \|A\| \quad (4.5)$$

Remark 4.10. For the special case that matrix A is regular, the pseudo inverse can be replaced with the inverse matrix and the condition number becomes:

$$\kappa(A) = \|A^{-1}\| \|A\| \quad (4.6)$$

Remark 4.11. Let A be a nonsingular matrix then a lower bound for the condition number is given by:

$$1 \leq \|I\| = \|AA^{-1}\| \leq \|A\| \|A^{-1}\| = \kappa(A)$$

Remark 4.12. Let $A \in \mathbb{R}^{m \times n}$ be a matrix and $\|\cdot\|_2$ the induced matrix norm. Then (4.5) simplifies to:

$$\kappa_2(A) = \frac{\sigma_{\max}(A)}{\sigma_{\min}(A)}$$

As already mentioned above, it is necessary to estimate to what extent changes in the input variables have an effect on the output variables. In the case of the calculation of an inverse matrix the following approach can be followed. Starting from a matrix A which should be inverted another matrix E is defined. This matrix E represents small changes of matrix A and should therefore be seen as perturbation of matrix A . In order to determine how numerically stable the inversion of a matrix A is, the following term is considered.

$$\|A^{-1} - (A + E)^{-1}\| \quad (4.7)$$

The task now is to find a constant c , so that for all sufficiently small matrices E it applies that:

$$\|A^{-1} - (A + E)^{-1}\| \leq c\|E\| \quad (4.8)$$

Remark 4.13. It can be shown that:

$$(A + E)^{-1} = (I + A^{-1}E)^{-1}A^{-1}$$

Corollary 4.1 ([AnaII]). *Suppose that B is a bounded linear operator on a Banach space X with $\|B\| < 1$. Then*

$$S = \sum_{k=0}^{\infty} B^k = (I - B)^{-1} \quad (4.9)$$

It therefore follows by applying remark 4.13 and corollary 4.1 that:

$$\begin{aligned} (A + E)^{-1} &= (I + A^{-1}E)^{-1}A^{-1} \\ &= (I - (A^{-1}E) + (A^{-1}E)^2 - (A^{-1}E)^3 + H.O.T.)A^{-1} \\ &= A^{-1} + A^{-1}EA^{-1} + H.O.T. \end{aligned}$$

For the estimation of the stability the following inequality can be obtained by using the previous results as well as (4.7):

$$\begin{aligned} \|A^{-1} - (A + E)^{-1}\| &= \|A^{-1} - (A^{-1} - A^{-1}EA^{-1} + H.O.T.)\| \\ &= \|A^{-1}EA^{-1} - H.O.T.\| \\ &\leq \|A^{-1}\|^2\|E\| + H.O.T. \end{aligned}$$

The relative error caused by applying a perturbation to matrix A has therefore an upper bound which is given by:

$$\frac{\|A^{-1} - (A + E)^{-1}\|}{\|A^{-1}\|} \leq \|A\|\|A^{-1}\|\frac{\|E\|}{\|A\|} + H.O.T. \quad (4.10)$$

Remark 4.14. *If the naturally induced spectral norm is used as the matrix norm, (4.10) simplifies to:*

$$\begin{aligned} \frac{\|A^{-1} - (A + E)^{-1}\|}{\|A^{-1}\|} &\leq \kappa_2(A)\frac{\|E\|}{\|A\|} + H.O.T. \\ &= \frac{\sigma_{max}}{\sigma_{min}}\frac{\|E\|}{\|A\|} + H.O.T. \end{aligned}$$

To reduce the influence of numerical instabilities, a linear least square problem is generally solved not by inverting the matrix of the normal equations like in step e) and iv) in algorithm (4) but by other numerical methods. A very frequently used method which avoids forming $A^T A$ and inverting it is the QR decomposition.

4. Non-negative least squares (NNLS)

4.2. QR - decomposition

A QR decomposition describes the decomposition of a matrix into a product of two matrices with special properties. This decomposition exists for every matrix and can be calculated with different algorithms where the best known are:

- Gram–Schmidt
- Householder transformation
- Givens rotations

Definition 4.4. Let $A \in \mathbb{R}^{m \times n}$ with $m \geq n$ be a matrix. The decomposition of A into a product $A = QR$ with an orthogonal matrix $Q \in \mathbb{R}^{m \times m}$ and an upper triangular matrix $R \in \mathbb{R}^{m \times n}$ is called a QR -decomposition of A .

Considering the fact that $m \geq n$ and the matrix R is always quadratic, it often makes sense to partition both R and Q in a way such that the special structure of these matrices can be used advantageously. Since R is an upper triangular matrix, the last $m - n$ rows of matrix R consist only of zeros. Therefore it makes sense to split the matrix Q into two parts Q_1 and Q_2 which have n and $m - n$ columns respectively. The QR decomposition is reduced by the use of the special characteristics described above to:

$$\underbrace{A}_{m \times n} = \underbrace{Q}_{m \times m} \underbrace{\begin{bmatrix} R_1 \\ 0 \end{bmatrix}}_{m \times n} = \begin{bmatrix} \underbrace{Q_1}_{m \times n} & \underbrace{Q_2}_{m \times (m-n)} \end{bmatrix} \underbrace{\begin{bmatrix} R_1 \\ 0 \end{bmatrix}}_{m \times n} = Q_1 R_1 \quad (4.11)$$

This notation is often referred to as reduced QR decomposition of A ([trefethen1997numer

Remark 4.15. The QR - decomposition is unique if $\text{rank}(A) = n$ and the diagonal elements of R_1 are required to be positive.

Remark 4.16. Let $Q \in \mathbb{R}^{n \times n}$ be an orthogonal matrix and $x \in \mathbb{R}^n$ a vector, then the following properties can be derived:

- $\|Qx\|_2^2 = (Qx)^T(Qx) = x^T Q^T Q x = x^T I x = \|x\|_2^2$ (length-invariant)
- $Q^T Q = I$

The QR -decomposition of matrix A can now be used to reduce the numerical instabilities that can occur in algorithm (4).

4.2. QR - decomposition

Remark 4.17. Let A^P be the restricted matrix from algorithm (4) and QR the corresponding decomposition such that $A^P = QR$. Then steps e) and iv) from algorithm (4) can be written as:

$$\begin{aligned}
 s^P &= ((A^P)^\top A^P)^{-1} (A^P)^\top b \\
 &= ((QR)^\top QR)^{-1} (QR)^\top b \\
 &= (R^\top Q^\top QR)^{-1} R^\top Q^\top b \\
 &= R^{-1} (R^\top)^{-1} R^\top Q^\top b \\
 &= R^{-1} Q^\top b
 \end{aligned} \tag{4.12}$$

A multiplication of (4.12) from the left with R results in a formula which is particularly easy for the calculation of the coefficients s_i^P .

$$Rs^P = Q^\top b \tag{4.13}$$

Since R is an upper triangular matrix, this system of equations can be solved very easily. Under the assumption that s^P has dimension $n \times 1$ and $Q^\top b$ is denoted as \tilde{b} , the parameters can be calculated by backward substitution following the rule:

$$\begin{aligned}
 s_n^P &= \frac{\tilde{b}}{r_{nn}} \\
 s_i^P &= \frac{1}{r_{ii}} \left(\tilde{b}_i - \sum_{j=i+1}^n r_{ij} s_j^P \right) \quad i = n-1, \dots, 1
 \end{aligned}$$

After showing how algorithm (4) benefits by using the QR decomposition, a way how such a decomposition can be calculated will be presented. In the following, the Householder-transformation, one of the most widespread methods, is derived.

4.2.1. Householder Transformation

The aim of the Householder transformation is to transform matrix A into an upper triangular matrix R by iterative multiplications of so-called Householder matrices H_i . The procedure is schematically shown in the following example:

4. Non-negative least squares (NNLS)

Example 4.2. Let $A \in \mathbb{R}^{m \times n}$, $m \geq n$ be the matrix for which a QR decomposition is to be performed. Let H_1 and H_2 be special Householder matrices. Then the QR decomposition is methodically calculated according to the following pattern.

$$\begin{aligned}
 A &= \begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & \cdots & a_{2,n} \\ a_{3,1} & a_{3,2} & \cdots & a_{3,n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m,1} & a_{m,2} & \cdots & a_{m,n} \end{pmatrix} \\
 H_1 A &= \begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ 0 & a_{2,2} & \cdots & a_{2,n} \\ 0 & a_{3,2} & \cdots & a_{3,n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & a_{m,2} & \cdots & a_{m,n} \end{pmatrix} = \begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ 0 & & & \\ 0 & & A_2 & \\ 0 & & & \end{pmatrix} \\
 H_2 H_1 A &= \begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ 0 & a_{2,2} & \cdots & a_{2,n} \\ 0 & 0 & \cdots & a_{3,n} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & a_{m,n} \end{pmatrix} = \begin{pmatrix} a_{1,1} & a_{1,2} & \cdots & a_{1,n} \\ 0 & a_{2,2} & \cdots & a_{2,n} \\ 0 & 0 & & \\ \vdots & \vdots & A_3 & \\ 0 & 0 & & \end{pmatrix}
 \end{aligned}$$

As shown in example (4.2), by applying the Householder matrix H_1 to matrix A , the first column of Matrix A is transformed to a multiple of the first unit vector. This transformation is implemented by a mirroring which is derived in the following section. After the transformation of the first column only the submatrix A_2 of the matrix $H_1 A$ is considered. This matrix consists of one row and one column less, but has a decisive advantage. Considering A_2 on its own, the first column can be mirrored to a multiple of the first unit vector as before and the same logic can be used iteratively. Altogether this means that the use of Householder matrices H_i iteratively generates an upper triangular matrix.

Remark 4.18. Since the sub matrices (i.e. A_2, A_3, \dots) that are to be transformed become in each step one row and one column smaller, this is also the case for the Householder matrices \tilde{H}_i . In order to preserve the transformations already carried out in the previous steps, the matrices \tilde{H}_i are therefore enlarged in a way such that:

$$H_i := \begin{bmatrix} I & 0 \\ 0 & \tilde{H}_i \end{bmatrix}$$

Figure 4.3.: Mirroring of \vec{x} to \vec{Px} through hyperplane H .

The task now is to find a matrix P that represents the desired reflection. To achieve this, a step-by-step approach is chosen. In a first step the reflection of a vector at a hyperplane through the origin in Euclidean space is constructed. Once this general case has been derived, it can be used to construct a reflection such that the first column of matrix A is transformed to a multiple of the first unit vector.

For the construction of the mirroring matrix P the case shown in figure (4.3) is considered. Let \vec{x} be a vector in an Euclidean space and \vec{Px} the vector into which \vec{x} is to be transferred by a mirroring. Furthermore, H is the hyperplane at which the reflection should take place. H , that mirror-hyperplane which runs through the origin is defined by the normal vector \vec{v} , thus a vector which is orthogonal to the hyperplane. The difference between the vector \vec{x} and the hyperplane H is called \vec{w} . The angle enclosed by the vectors $-\vec{x}$ and \vec{w} is called θ . The goal is to identify a relation between \vec{Px} and \vec{x} . In the sense of better readability and since there can be no misunderstandings in the following, the vector arrows are omitted from now on. The length of \vec{w} is then given by:

$$\|w\| = \|x\| \cos(\theta) = \|x\| \frac{\langle -x, v \rangle}{\| -x \| \|v\|} = \frac{-x^\top v}{\|v\|}$$

Where in the second step the definition of the dot product was used. The vector w is then characterized by the length and the direction which leads to:

$$w = \frac{-x^\top v}{\|v\|} \frac{v}{\|v\|} = -v \frac{x^\top v}{v^\top v}$$

4. Non-negative least squares (NNLS)

By referencing to figure (4.3), the mirrored vector Px can now be defined as:

$$Px = x + 2w = x - 2v \frac{x^\top v}{v^\top v} = x - 2 \frac{vv^\top x}{v^\top v} = \left(I - 2 \frac{vv^\top}{v^\top v} \right) x$$

The matrix constructed, representing the linear mapping described above is called Householder matrix. Householder matrices are defined by a normal vector v , i.e. a vector that is orthogonal to the mirror hyperplane and are typically denoted by H .

$$H = I - 2 \frac{vv^\top}{v^\top v} \quad (4.15)$$

Where I in equation (4.15) is the identity matrix. In case that v is normalized to length one (4.15) simplifies to:

$$H = I - 2vv^\top \quad (4.16)$$

The concept of Householder matrices can now be used to formalize the process described in example 4.2. Let x be a vector which is to be mirrored to a multiple of the first unit vector e_1 . This means that a vector v is required, so that with the corresponding Householder-Matrix H_v the following linear transformation can be achieved.

$$H_v x = ce_1$$

The required reflection vector v now results from normalizing the difference vector and is given by:

$$v = \frac{x - ce_1}{\|x - ce_1\|}$$

A basic property that is important for the construction of a QR decomposition is the fact that Householder matrices are orthogonal.

Remark 4.19. *Let H be a Householder matrix. Then H is symmetric and orthogonal.*

$$H^\top = \left(I - 2 \frac{vv^\top}{v^\top v} \right)^\top = I^\top - \left(2 \frac{vv^\top}{v^\top v} \right)^\top = I - 2 \frac{(vv^\top)^\top}{(v^\top v)^\top} = I - 2 \frac{vv^\top}{v^\top v} = H$$

$$\begin{aligned}
H^\top H &= HH = (I - 2\frac{vv^\top}{v^\top v})(I - 2\frac{vv^\top}{v^\top v}) \\
&= I^2 - 2I\frac{vv^\top}{v^\top v} - 2I\frac{vv^\top}{v^\top v} + 4\frac{vv^\top}{v^\top v}\frac{vv^\top}{v^\top v} \\
&= I - 4\frac{vv^\top}{v^\top v} + 4\frac{vv^\top vv^\top}{v^\top vv^\top v} \\
&= I - 4\frac{vv^\top}{v^\top v} + 4\frac{(v^\top v)vv^\top}{(v^\top v)^2} \\
&= I
\end{aligned}$$

Remark 4.20. Let H_1, H_2, \dots, H_n be Householder matrices as stated in example 4.2. Then by using the properties proofed in the previous remark the QR decomposition is given by:

$$\begin{aligned}
&H_n H_{n-1} \cdot \dots \cdot H_1 A = R \\
\Leftrightarrow &Q^\top A = R \\
\Leftrightarrow &QQ^\top A = QR \\
\Leftrightarrow &A = QR
\end{aligned}$$

After demonstrating how a QR decomposition can be performed using Householder transformations, the next section is dedicated to the question of performance.

4.2.2. Performance

Even if runtime analyses of algorithm 4 have shown that a large part of the computing time had to be dedicated to the calculation of the gradients, the importance of finding the solution for the least square problems must not be underestimated and will therefore be analyzed as well. Since not only computing time but also the numerical stability of the grouping process is of great interest in practice, the runtimes and accuracies of different approaches for solving the least squares problem are compared in this section. Obviously, an implementation of a grouping algorithm which is numerically stable on the one hand and fast on the other hand with regard to the computing time is the preferred solution. Therefore seven different implementations will be compared using only functions that are available in R by default. Since these are standard functions in the area of linear algebra, it can be assumed that the functions used

4. Non-negative least squares (NNLS)

are optimized with regard to performance. In particular, some functions access implementations of the software packages LINPACK and LAPACK directly and therefore act only as wrappers. Examples of such R-functions are `solve` and `qr` whose default methods are interfaces to the LAPACK routine DGEVS and ZGESV as well as DQRDC from the LINPACK package.

- DGEVS computes the solution to a real system of linear equations $A * X = B$, where A is an N-by-N matrix and X and B are N-by-NRHS matrices [`lapack`].
- DQRDC uses householder transformations to compute the qr factorization of an n by p matrix x. column pivoting based on the 2-norms of the reduced columns may be performed at the users option [`linpack`].

The two software libraries LINPACK and LAPACK are written in Fortran and enjoy great popularity in many areas of application due to their efficient implementations with respect to memory usage and computational speed. Of course, there is also a big number of packages available on CRAN (Comprehensive R Archive Network) that offer different implementations for solving least square problems. Since a comprehensive analysis of these implementations is not possible due to the daily growing number of packages available, the focus is on standard functions available in R. The R-functions used to perform the comparison are `solve`, `backsolve`, `qr.solve`, `qr` and `t`. The notation used in algorithm 4 steps e) and iv. is simplified for the following comparison to the degree that the restriction to set P is not explicitly specified, i.e. $A^P = A$. The first three approaches pursue a solution without the calculation of a QR decomposition whereas the last four approaches are based on a QR decomposition.

Method 1: This method uses the calculation procedure for solving a least square problem given in algorithm 4 which is defined as:

$$s = (A^\top A)^{-1} A^\top b$$

```
solve((t(A) %*% A)) %*% t(A) %*% b
```

Method 2: For this method, the initial approach from the previous method is transformed in such a way that no inverse has to be calculated any more. The least squares problem is then given by:

$$(A^\top A)s = A^\top b$$

```
solve(t(A) %*% A, t(A) %*% b)
```

Method 3: The last approach using no *QR* decomposition solves the least squares problem using the `crossprod` function. This function calculates the cross product and according to the documentation should be slightly faster than a direct calculation via the transposed matrix. The approach is therefore identical to the one from method 2 except that a different implementation is used.

$$(A^T A)s = A^T b$$

```
solve(crossprod(A), crossprod(A,b))
```

Method 4: This approach uses a *QR* decomposition and directly implements formula (4.12) derived in remark ?? for the solution of the least squares problem.

$$s = R^{-1}Q^T b$$

```
deco <- qr(A, LAPACK = FALSE)
solve(qr.R(deco)) %*% t(qr.Q(deco)) %*% b
```

Method 5: This approach again uses a *QR* decomposition and applies formula (4.13), which is a transformation of formula (4.12). Therefore no inverse has to be calculated to solve the least squares problem

$$Rs = Q^T b$$

```
deco <- qr(A, LAPACK = FALSE)
solve(qr.R(deco), t(qr.Q(deco)) %*% b)
```

Method 6: This method again uses a *QR* decomposition, but also makes use of the special form of the decomposition where *R* is an upper triangular matrix. The function `backsolve` solves a system of linear equations where the coefficient matrix is upper triangular [**R**].

$$Rs = Q^T b$$

4. Non-negative least squares (NNLS)

```
deco <- qr(A, LAPACK = FALSE)
backsolve(qr.R(deco), t(qr.Q(deco)) %*% b)
```

Method 7: The last method uses a QR decomposition as well. The result of the QR decomposition is not saved in a temporary variable as before, but is passed directly to the `qr.solve` method.

$$QRs = b$$

```
qr.solve(qr(A, LAPACK = FALSE), b)
```

In order to determine how the number of columns of matrix A affects the run time, the following setup was chosen. Matrix A was defined as a square matrix with $n = 5000$, where the entries of A is uniformly distributed between 0 and 100000, i.e. $A \in R^{n \times n}$. The values of vector x are uniformly distributed between 0 and 1000. By defining matrix A and vector x , the result vector b is determined as well. For each of the seven methods, the number of columns used from matrix A was successively increased and then the least squares problem was solved. Figure (4.4) shows how the time needed to solve the least squares problem increases with the number of columns.

Intel[®] Core[™] i7-6700 processor with 64GB of RAM.

4.2. QR - decomposition

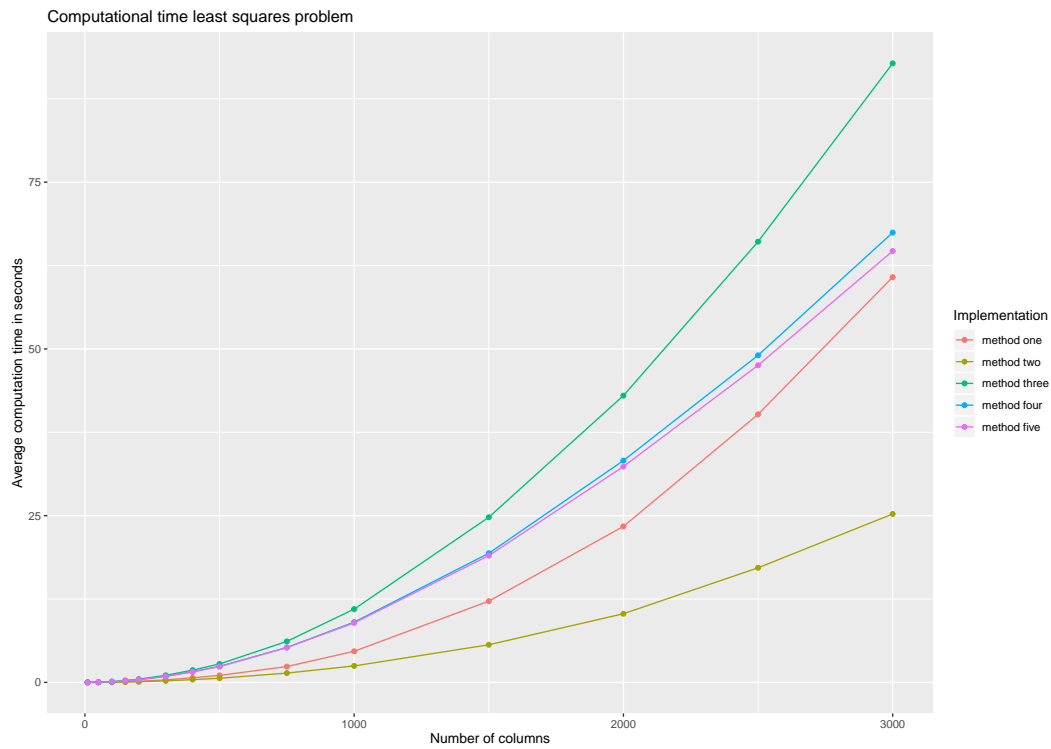


Figure 4.4.: Computation time for solving the least squares problem $Ax = b$ in seconds.

Appendix A.

Tables

test

month	pop_15	pop_70	prem_15	prem_70	prem_diff	claims_15	claims_70	claims_diff
0	1	1						
9	0.999834	0.987259	385.60	1128.40	742.80	1.70	130.61	128.91
21	0.977140	0.947577	379.73	1092.63	712.90	4.73	185.70	180.97
33	0.952445	0.905554	370.17	1045.64	675.47	10.08	201.42	191.34
45	0.928273	0.863652	360.80	998.80	638.00	15.22	216.81	201.60
57	0.904661	0.821842	351.64	952.09	600.45	19.87	232.12	212.25
69	0.881638	0.780093	342.69	905.48	562.79	24.11	247.29	223.18
93	0.837332	0.696652	325.47	812.40	486.93	32.45	277.16	244.71
105	0.816021	0.654913	317.19	765.86	448.68	36.70	291.89	255.19
117	0.795253	0.613146	309.11	719.31	410.19	41.02	306.32	265.29
129	0.775013	0.571358	301.25	672.72	371.47	45.41	320.21	274.81
141	0.755288	0.529577	293.58	626.11	332.54	49.85	333.38	283.53
165	0.717332	0.446430	278.82	533.03	254.20	58.90	354.70	295.80
177	0.699076	0.405693	271.73	486.94	215.21	63.50	359.06	295.56
189	0.681284	0.365984	264.81	441.73	176.92	68.15	359.15	291.01
201	0.663944	0.327583	258.07	397.76	139.68	72.83	355.49	282.66
213	0.647046	0.290722	251.51	355.31	103.81	77.54	348.61	271.07
237	0.614523	0.222339	238.87	275.96	37.09	87.12	326.91	239.79
249	0.598856	0.191115	232.78	239.40	6.62	91.79	312.50	220.71
261	0.583562	0.162081	226.85	205.15	-21.70	96.52	295.62	199.10
273	0.568621	0.135426	221.05	173.38	-47.67	101.35	276.01	174.66
285	0.554015	0.111340	215.39	144.32	-71.07	106.29	253.63	147.35
297	0.539728	0.089980	209.85	118.16	-91.69	111.28	228.95	117.68
309	0.000000	0.000000	0.00	0.00	0.00	5983.32	991.18	-4992.14

Table A.1.: Yearly outputs for PVFP-sensitivity analysis based on an interest rate of 2%.

Appendix B.

Code

```
1 # The pseudocode for the nnls-algorithm can be found at
2 # https://en.wikipedia.org/wiki/Non-negative\_least\_squares
3 nnls_VMF <- function(A, b, Modellpunkte = 0, Fehlertol = 1e-10, MainloopMax =
4   10000, InnerloopMax = 1000, Ausgabe = 0) {
5   N <- dim(A)[2]
6   # Count the number of zeros per row; if for one row there are N zeros all
7   # policies
8   # produce zeros for that cashflow --> not a relevant information.
9   AnzNull <- rowCounts(A, value = 0)
10  # find those rows which have non-zero values in A and b simultaneously
11  # Those rows have relevant information
12  Zeilen <- (AnzNull != N) & (b != 0)
13  # Reduce A and b to those rows with relevant information
14  A <- A[Zeilen,]
15  b <- b[Zeilen]
16
17  # Initialize
18  P <- NULL
19  R <- 1:N
20  x <- rep(0, N)
21
22  # Log the number of non-zero entries in x by counting the elements in P
23  nonZeroEntries <- length(P)
24
25  # Log the development of the residuals
26  fitted <- A %*% x
27  residual_tmp <- (b - fitted)^2 %>% sum()
28
29  # Calculate initial Gradient "t(A) %*% (b - A %*% x)"
30  # Since in first iteration x is zero this simplifies to "t(A) %*% b"
31  w <- crossprod(b, A)
32  # Find highest descent
33  wmax <- max(w)
34  Stellen <- -log(Fehlertol, 10)
35  # initialize counter for Main loop
36  Mainloop <- 0
37
38  # initialise variables for the exit-reason
39  jprev <- 0
40  Stabiler_Zustand <- 0
41  Abbruch_Grund <- 0
```

Appendix B. Code

```
42 # define the tolerance based on the machine precision
43 TestTol <- .Machine$double.eps * 1000
44
45 # When the user doesn't restrict the number of modelpoints then
46 # we set the number of maximal modelpoints to the number of variables we
47 # want to match.
48 if (Modellpunkte == 0) {
49   Modellpunkte <- dim(A)[1]
50 }
51 ModellpunkteMax <- min(2*Modellpunkte, dim(A)[1])
52
53 # initialize progress bar
54 pb <- winProgressBar(title = "Progress",
55                       min = 0,
56                       max = Modellpunkte,
57                       width = 600)
58
59 # Mainloop
60 while ((length(P) < ModellpunkteMax) &
61        (Mainloop < MainloopMax) &
62        (Stabiler_Zustand == 0) &
63        (wmax > Fehlertol)) {
64
65   # log development of residuals
66   fitted <- A %*% x
67   resid <- b - fitted
68
69
70   Stabiltest <- 0
71   while (Stabiltest == 0) {
72     j <- which.max(w[R])
73     Kandidat <- R[j]
74     Ptemp <- unique(sort(rbind(P, Kandidat)))
75     # check if det below tolerance, if this is the case then we can't invert
76     # t(A) %*% A restricted to the columns of P
77     if (det(crossprod(A[,Ptemp])) <= TestTol) {
78       w[Kandidat] <- 0
79     } else {
80       Stabiltest <- 1
81     }
82   }
83
84   # if the new candidate is the same as in the last iteration of the loop
85   # a stable state is reached and the optimization is finished
86   if (R[j] == jprev) {
87     #Stabiler_Zustand <- 1
88   }
89
90   #if (Stabiler_Zustand == 0) {
91     if (0 == 0) {
92       jprev <- R[j]
93
94       # move index form R to P
95       P <- unique(sort(rbind(P, R[j])))
96
97       # define restricted matrix A^P
98       AP <- A[, P]
99       s <- rep(0, N)
100       # compute the restricted least squares problem
101       sP <- solve(crossprod(AP), crossprod(AP, b))
```

```

102 #       sP <- solve( t(AP) %*% AP, t(AP) %*% b)
103 #       sP <- as.matrix(lsfrit( AP, b, intercept = FALSE)[[1]])
104 # assign the results of the restricted least sqaures problem to the
105 # entries of s indexed in P.
106 s[P] <- sP
107 Innerloop <- 0
108
109 # Innerloop
110 while ((min(sP) <= 0) & (Innerloop < InnerloopMax)) {
111   # find indices for negative values
112   neg <- P[sP <= 0]
113   alpha <- min (x[neg] / (x[neg] - s[neg]), na.rm = TRUE)
114   x[P] <- x[P] + alpha * (s[P] - x[P])
115
116   temp <- (round(x[P], Stellen) != 0)
117   AP <- AP[temp]
118   P <- P[temp]
119   sP <- solve( crossprod(AP), crossprod(AP, b))
120   #       sP <- solve( t(AP) %*% AP, t(AP) %*% b)
121   #       sP <- as.matrix(lsfrit( AP, b, intercept = FALSE)[[1]])
122   s <- rep(0, N)
123   s[P] <- sP
124   Innerloop <- Innerloop + 1
125 } # End Innerloop
126
127 R <- (1:N)[-P]
128 x <- s
129 w <- crossprod(b - AP %*% sP, A)
130 wmax <- max(w)
131 Mainloop <- Mainloop + 1
132
133
134 # logging
135 nonZeroEntries <- rbind(nonZeroEntries, length(P))
136 # Log the development of the residuals
137 fitted <- A %*% x
138 residual_tmp <- c(residual_tmp, (b - fitted)^2 %>% sum())
139
140
141
142 setWinProgressBar(
143   pb,
144   length(P),
145   title = paste0("Policies ", length(P), " of max. ", Modellpunkte,
146                 " Mainloop: ", Mainloop, " max(w): ", round(wmax, 4)
147 )
148 )
149 } # End Stabiler_Zustand
150 } # End Mainloop
151
152 # close progress bar
153 close(pb)
154
155 # Apply fit and calculate residuals
156 fitted <- A %*% x
157 resid <- b - fitted
158
159 if (Stabiler_Zustand == 1) {
160   Abbruch_Grund <- "stable state"
161 }

```

Appendix B. Code

```
162 else if (Mainloop >= MainloopMax) {
163   Abbruch_Grund <- "main loop max reached"
164 }
165 else if (max(w) <= Fehlertol) {
166   Abbruch_Grund <- "gradient too small"
167 }
168
169 xepsilon <- x
170 Pepsilon <- (1:N)[xepsilon > Fehlertol]
171 xepsilon[xepsilon <= Fehlertol] <- 0
172
173 nnls_VMF.out <- list(
174   x = x,
175   xepsilon = xepsilon,
176   deviance = sum(resid ^ 2),
177   residuals = resid,
178   fitted = fitted,
179   mw = max(w),
180   w = w,
181   passive = P,
182   Pepsilon = Pepsilon,
183   loops = Mainloop,
184   nsetp = length(P),
185   Abbruch = Abbruch_Grund,
186   Entwicklung = nonZeroEntries,
187   Residual_Entwicklung = residual_tmp
188 )
189
190 class(nnls_VMF.out) <- "nnls"
191 nnls_VMF.out
192 } # End nnls_VMF
```

Listing B.1: Implementation of Lawson and Hanson NNLS algorithm in R

The todo text is the text that will be shown in the todonote and in the list of todos. The optional argument options, allows the user to customize the appearance of the inserted todonotes. For a description of all the options see sadf The todo text is the text that will be shown in the todonote and in the list of todos. The optional argument options, allows the user to customize the appearance of the inserted todonotes. For a description of all the options see The todo text is the text that will be shown in the todonote and in the list of todos. The optional argument options, allows the user to customize the appearance of the inserted todonotes. For a description of all the options see The todo text is the text that will be shown in the todonote and in the list of todos. The optional argument options, allows the user to customize the appearance of the inserted todonotes. For a description of all the options see fasd fadsf asdf

Make a cake ...



Make a sketch of the structure of a trebuchet.