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Personalizing the Austrian inflation rate

DIPLOMA THESIS

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Declaration of Authorship

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I hereby declare that I have written this Thesis independently, that I have completely specified the utilized sources and resources and that I have definitely marked all parts of the work - including tables, maps and figures - which belong to other works or to the internet, literally or extracted, by referencing the source as borrowed.

Vienna, 15th January, 2018

Tomislav Tvrdic

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Abstract

Inflation is one of the most prominent key economic indicators. It is present in daily lives of every citizen in the form of change of prices of items or services which they purchase. This work argues that the problem is that citizens often misinterpret the relationship between inflation and their consumption because they usually have a distorted image on price dynamics of items consumed, as well as their share in the personal consumption basket. These arguments lead to an overall distrust of inflation as a measure, and subsequently, in the national statistics offices that produce it. Statistics offices tackled the problem by creating personal inflation calculators that require citizens to input their exact consumption pattern. This thesis defines and builds on the uninformed user hypothesis, which argues that most citizens do not have a real image of how they are spending their disposable income.

The central focus of this work is to define a model that takes this hypothesis and creates a set of constraints and requirements to bypass the problem of people not knowing their consumption patterns. The approach of requiring the uninformed users to input their accurate consumption data is replaced by constructing a model using machine learning methods. This model is then used to build a survey which aims at decreasing question complexity, thus reducing user input error, outputting a consumption pattern scheme which is then used to calculate a personal inflation rate. This will be achieved by building a model using Multivariate decision tree regression. In the end, this could be a way to recoup lost mistrust in official price statistics. Furthermore, this thesis uses the power of data visualization to provide an interpretive framework to both citizens and researchers.

The results of this work show how a robust baseline model is established, which, however, lacks a comparative benchmark to determine the validity of assumptions on which it is built. Nonetheless, it serves as a motivation to both improve the model and use it for educative and research purposes.

Keywords: Inflation, Personalized Inflation, Consumption, Prices, Data Visualization, Machine Learning, Decision Trees, Multivariate Regression

Kurzfassung

Neben dem Wirtschaftswachstum und der Arbeitslosenrate ist die Inflation eine der zentralen ökonomischen Kenngrößen einer jeden Volkswirtschaft. Diese Arbeit geht davon aus, dass Konsumenten eine verzerrte Wahrnehmung von Inflation haben, insbesondere da die individuellen Verbrauchsgewohnheiten nicht mit dem nationalen Durchschnitt vergleichbar sind. Daher wird die Inflation mit einem gewissen Argwohn betrachtet, was dazu führen kann, dass das Vertrauen in offizielle Statistiken abnimmt. Statistikämter versuchen dem entgegenzutreten, indem sie persönliche Inflationsrechner zur Verfügung stellen, mit dem der einzelne Bürger seine eigene Inflationsrate gemäß seiner individuellen Verbrauchsstruktur berechnen kann. Dies setzt aber voraus, dass letztere auch bekannt ist. Dies Arbeit geht hingegen von der Hypothese des uninformierten Nutzers aus, welche besagt, dass die meisten Bürger kein klares Bild davon haben, wie sie ihr zur Verfügung stehendes Einkommen ausgeben.

Der Schwerpunkt dieser Arbeit liegt darauf, ein Modell auf Basis dieser Hypothese zu erstellen sowie Rahmenbedingungen und Anforderungen derart vorzugeben, um dieses Problem des unwissenden Nutzers zu umgehen. So ist es nicht mehr notwendig, dass uninformierte Nutzer Konsumdaten zur Berechnung der persönlichen Inflationsrate angeben müssen. Stattdessen wird ein Modell erstellt, das die Methoden des maschinellen Lernens verwendet. Anschließend wird dieses Modell dafür genützt, um Fragen das Konsummuster der einzelnen Person betreffend so zu stellen, dass die Eingabefehler der Nutzer verringert werden. Für die Schätzung des Modells werden multivariate Entscheidungsbaum-Regression verwendet. Darüber hinaus entwickelt diese Arbeit ein Tool zur Visualisierung und Analyse von Inflationsstatistiken, das es den Anwendern erlaubt, die Daten besser interpretieren zu können.

Die Ergebnisse dieser Arbeit zeigen, wie ein robustes Basismodell erstellt wird, dem allerdings ein Vergleichsmaßstab noch fehlt, um die Validität der Annahmen, die für seine Herstellung verwendet wurden, zu überprüfen. Dennoch dient es als Motivation für die Verbesserung des Modells sowie für die Verwendung für Bildungs- und Forschungszwecke.

Schlüsselwörter: Inflation, personalisierte Inflationsrate, Verbraucherpreise, Datenvisualisierung, Maschinelles Lernen, Entscheidungsbäume, multivariate Regression

Contents

CHAPTER 1

Introduction

"Inflation is as violent as a mugger, as frightening as an armed robber and as deadly as a hit man."

- Ronald Reagan, *1978*

What is inflation? As defined by the European Central Bank, it is the broad increase in the prices of goods and services, not just for the individual items [1]. According to its very definition, the inflation measurement encompasses the average spending habits of all households together; bundling them together to identify consumer preferences.

In Austria, the basis for inflation measurement is a budget of a representative household and its average expenditure for a wide range of 789 goods and services [2][3]. It is important to note here that not only frequently consumed items are considered (food, gasoline, etc.) but also durables (such as cars, mobile phones) and services (travel, insurance, etc.).

Based on this basket, price information is collected in 3,500 shops of the 20 biggest Austrian towns for around 40,000 individual item prices [2]. They are then translated into a price index, which uniformly identifies the price measurement of a product. The next step is to assign contribution weights to each item from the consumption basket of an average consumer, which represents their share in household expenditure. They are then combined with items' price indexes, as well as their comparison to previous year's indexes, as the basis of calculating the inflation rate.

In Europe there are two different inflation measures, according to the goods which are part of the earlier mentioned consumers' basket; namely the Harmonised Indices of Consumer Prices (HICP) and Consumer Price Indices (CPI). HICP is defined by the European Central Bank (ECB) to provide a uniform inflation definition on the level of the entire European Union, and as such is comparable between different state members [4]. CPI, on the other hand, varies between countries, since it is tailored to the specific role in the countries' monetary policy [5].

Austrian CPI is used as a general price trend and inflation measure in Austria and as such is a basis of wage and salary negotiations. CPI, as well as HICP, is revised on a five-year basis; the aim is to adapt the representative consumption basket along with the included weights [6].

In this thesis, the HICP measure is used as the inflation data from Eurostat, the data source used for developing this work, is based on this inflation measure. Moreover, it is the data basis for the development of two artifacts of this thesis. The first one, inflation visualization and analysis tool, combines the HICP price indices with consumption weights of an average Austrian consumer to calculate the official inflation rate for Austria. The same process is applied to other countries' weights and price indices, forming an inflation visualization tool, the goal of which is supporting the reasoning and analysis process. The second artifact combines the same HICP price indices with the outcome of personal consumption estimation using the model which will be presented and evaluated in Chapters 3 and 5. Since this model yields a weighting scheme based on user input, combining it with price indices produces a personal inflation estimate.

1.1 Relevance of inflation

Shiller [7] stated almost two decades ago that the term "inflation" seems to be the most popular macroeconomic term among the general public, beating such terms as "unemployment", "productivity" or "growth". Albeit reduced due to recent trends, the relevance of inflation as critical macroeconomic indicator still holds today; it is best expressed in the perception and expectation that the economic subjects have on it, and as such can have a vast number of influences on the entire economy. Because members of the society are active parts of any macroeconomic framework, the way their expectations about price dynamics are shaped, combined with the relevance their consumption habits based on those expectations are formulated, this is indeed one of the critical elements of forecasting macroeconomic trends and formulating the monetary policy [8]. It is for this reason that the difference between the actual inflation rate and the one perceived by individuals is an essential topic of this thesis. Moreover, Vogel et al. [9] argue that having a significant gap between what the population understands to be the inflation rate and the actual figures can significantly undermine the credibility of the central bank. Furthermore, these factors then lead to difficulties in setting crucial economic policy points, as the rationality of agents seems to be narrowed due to these differences in perception of key economic indicators.

Donovan [10] and O'Donogue et al. [11] also mention the value of trust in inflation statistics. These works state that there seems to be a general mistrust in statistical reports on inflation, which eventually leads to investor uncertainty, ultimately damaging the economy. This hypothesis is further strengthened by works of Stevenson [12], who also highlights the distrust of UK citizens to official inflation statistics in his article. The response of the UK National Statistics Office to this distrust was the creation of a personal inflation calculator, to give the citizens means to inform themselves about an inflation rate more appropriate to their consumption pattern. Interestingly, Stevenson also speculates that this higher level of information "may be the stick to beat employers", as a better level of information will put the employees and syndicates ahead in the wage bargaining discussions with their employers.

1.2 Inflation perception

In the previous section, it has been established that inflation perception and expectations tied to it are some of the essential elements in macroeconomic forecasting and policy decisions. Thus, the first question that arises is how is inflation perceived; moreover, which are the relevant factors which influence the inflation perception.

Brachinger [13] states that there is, in fact, no such thing as a "true inflation". The intent behind this statement is to introduce the interpretative framework which is based on series of assumptions, acknowledging the existence of the notion of perception of reality on which these assumptions are based.

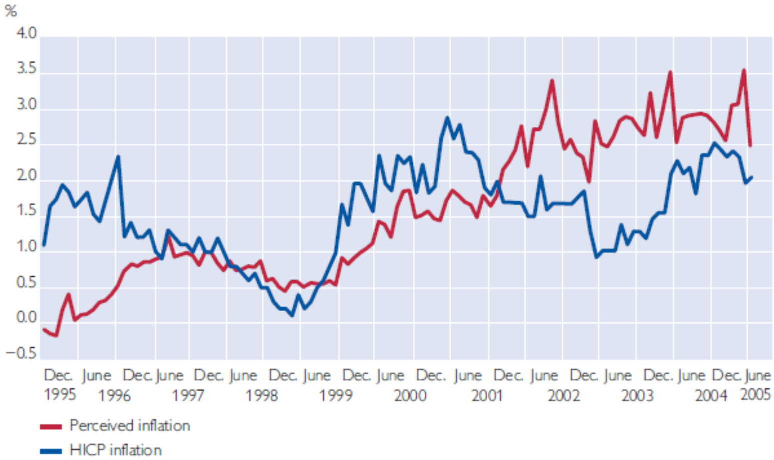
Brachinger establishes two interpretative frameworks; the first of which is based on a consumers' perspective, where the consumption of certain goods in a given time frame is of relevance. This framework is a rigid, "perfect information", which is freed of biases and perceptions, and as such is based on hard facts on consumption patterns in a measured period. This perspective provides the basis for the calculation of CPI and HICP and corresponds to the consumption survey used in this thesis.

The second interpretative framework is a more fluid one since it is based on purchaser's perspective, where the act of purchasing specific goods in a given time frame is of relevance. The definition of this view argues that the purchaser is more biased regarding the inflation perception because a good which is purchased more often appears to carry more relevance from the purchaser's perspective.

The outcome of the assumptions of the latter framework is measured by the Index of Perceived Inflation - IPI [13] which aims to capture the extent of bias that the consumers have on the current inflation rate.

In Austria, perceived inflation is estimated by leveraging data from the Consumer confidence barometer [13]. The exact question asked by the survey is "How do you think that consumer prices have developed over the last 12 months?". Answers in the range of a) "risen a lot", b) "risen moderately" c) "risen slightly" d) "stayed about the same" e) "fallen" and f) "I don't know" are offered. Once the answers are gathered and their percentile weight calculated, formula (1.1) is applied.

$$balance = \%(a) + 0.5 * \%(b) - 0.5 * \%(d) - \%(e) \tag{1.1}$$



Source: Consumer Confidence Barometer of the European Commission, Statistics Austria

Figure 1.1: Actual versus perceived (IPI) inflation in Austria

This sets the stage to the cornerstones of this thesis; the first one being the difference between the perceived and actual inflation, and the second one is the identification of individual consumption patterns, and the personalized inflation based on it.

The former relies on Brachinger's [13] second framework hypothesis, which will be further expanded with additional parameters (such as demographics or media communications) that determine the purchaser's bias. The latter relies on the first hypothesis, as the Austrian Consumption Survey data will be used to individualize the consumption pattern of a single user; thus establishing an unbiased personal consumption estimation.

Table 1.1 provides a compact overview on the differences between inflation rate collected by HICP and CPI, aggregating the Austrian consumption survey into a single representative user and the perceived inflation, based on the European Consumer Confidence Barometer.

The question at hand is: what are the factors that influence one's perception of inflation?

There are multiple theories which discuss the reasons behind the differences in the IPI and HICP graph; ranging from data collection bias [14][15], major financial change such as the introduction of Euro currency for European Union (EU) countries [16][17][2][13][18], loss aversion [13], demographics [2] and personal experience [19].

De Bruin, Van der Klaauw, and Topa [14] argue that formulation of inflation expectation and perception is conditioned by the survey questions when this information is gathered. In their work, they have presented two studies whose primary focus was to determine whether the extremeness on individuals' inflation expectation was biased by a consideration of an example of extreme price change in the last 12 months. Their results

Criteria	HICP/CPI	Perceived Inflation
Level	whole economy	individual consumer
Household	average household	individual household
Prices observed / basket	about 800 representative goods and services	convenience goods
Region	20 Austrian towns and cities	local shops
Weighting	according to expenditure shares derived from consumer surveys and national accounts, expert advice	possibly according to the frequency of purchase
Price Collection	about 40,000 per month	during the act of buying
Calculation	all price changes (weighted) translated into an index	based on surveys on the public's estimation of price developments over the last 12 months
Methodology	Laspeyres index, for HICP modified and translated into a chain index	weighted percentage balance between "prices have risen" and "prices have fallen" responses, conversion into perceived inflation rate
Use	established and widely used indicator for economics, economic statistics (monetary policy, wage policy)	monetary policy: estimates of inflation by consumers, inflation expectations
Availability	published monthly	monthly, published on the Internet
Public perception	press releases, contracts	consumers' purchases

Source: OeNB

Table 1.1: Actual and perceived inflation, difference in methodology

suggest that acute price changes of individual items affect and skew the overall picture of inflation, influencing the total perceived inflation reports.

Inoue et al. [15] state that implicit expectations have a higher predictive power on CPI inflation than survey responses, especially with a lower educated population. Providing evidence in the form of consumption data analysis, they speculate that "Actions speak louder than words", in other words, that the households take an active stand on inflation expectations by trading off future against current consumption.

There is a significant body of work on the effect that introduction of Euro as a monetary unit in selected European Union Countries in 2001 has had on the perception of consumer prices. These articles are mainly interesting due to the extremity of differences between nominal inflation rate and the one perceived by the general public in those countries.

Traut-Mattausch et al. [17] focused on the role of a priori expectations. In their work, they argued that before the introduction of Euro there was a fear present among the members of the general public, that abuse and price manipulation will be a result of the cash changeover [16]. This fear eventually leads to a bias towards perceiving the prices of goods and services after the introduction of Euro, leading to a higher perception of inflation [20]. This has lead to a "Euro - Teuro" (A wordplay in German, where "teuer" stands for "expensive") media campaign, which was present in Austria around the time Euro was introduced. The HICP inflation numbers, however, have shown that inflation has not increased significantly, and has, in fact, decreased from 1.8% in 2002 to 1.3% in 2003 [2]. The damage to the image of the new European currency was, however, already done, mostly because of the gap between perceived and actual inflation rate, the damage being evident the most in Italy [21].

Another interesting point regarding the distorted inflation perception was the lack of proper estimation for the value of Euro in the period after its introduction. In a survey that was conducted in Austria in 2004, 2 and a half years after the introduction of Euro, about 13% of Austrians stated that they still always converted prices into Schilling. Furthermore, 27% said they did so often and 34%, sometimes, and only 26% reported that they never convert the prices [22]. This has a two-fold effect; firstly, the error in inflation perception is introduced because of the conversion process which might not always be accurate with the average consumer. Secondly, the conversion rate, as well as reference prices 30 months after the Euro, was introduced were outdated, and as such did not experience dynamics that Euro has seen after the changeover [13].

The same survey showed that 57% of the participants thought that all prices were higher than three years before and 35% thought this was limited only to some products. Only 7% believed that the price changes were minimal or nonexistent [22]. 59% of the participants named the Euro introduction as the primary cause for the prices increase.

An unfortunate coincidence for the erosion of acceptance of Euro was that some prices did grow significantly; at the beginning of 2002, there has been a 6.7% increase in prices of foodstuffs. The reason for this increase, however, was a particularly harsh winter in the southern European fruit- and vegetable-producing areas [13].

These were examples how an external shock such as the introduction of a new currency in a country could affect price and, therefore, inflation perceptions. Such events, however, occur rarely and irregularly. Brachinger and Powell both argue that there is a regular factor which distorts how the consumers perceive a price level in a country, based on the frequency of their purchase [13][23].

In the summer of 2004, a survey was conducted in Austria which aimed to detect which price category seemed to upset Austrian citizens the most. Respondents indicated food (21%), followed by fuels (17%), hotels and restaurants (13%) and convenience goods (7%). Services and textiles, for example, were named by only around 3% of the participants [22]. These results pointed towards the conclusion that goods which are purchased on a daily basis, such as food, seem to induce more sensitivity to price change among consumers; as opposed to, for example, services, which are usually not consumed on an occasional basis.

Brachinger links this effect to the Prospect theory [24], claiming that loss aversion implies that consumers' inflation perceptions are more influenced by price increases than by price decreases. Adding that hypotheses to the availability hypothesis that price changes are perceived at the moment when a good is bought [25] [13], leads us to two conclusions:

1) Prospect theory is reflected in the fact that individuals evaluate a price change against a reference price [9], which can be determined either by the consumers' perception a fair price [26] or Brachinger's [13] suggestion of a past price.

2) Availability hypothesis implies that the perception of a price change for a good or service that is bought more often is stronger than the one which is purchased less frequently, leading to the conclusion that perceived inflation is higher when the price of former is rising faster than the cost of the latter. Furthermore, studies by Tversky and Kahneman [27] and Jungermann et al. [28] have shown that availability hypothesis can also be seen in the increase of price perception of cheaper products.

Stix [29] proved the assumptions by analyzing consumption survey data, assuming a person that runs a household is more exposed to a higher inflation perception bias formed by purchasing everyday household goods than a person not responsible for running one. Vogel et al. [9], found that not only the availability hypothesis is confirmed, but also that less frequently purchased items had their share of significance in the overall inflation perception, attributed to the global consumers' awareness of inflation after the introduction of Euro.

The conclusions brought forward by Brachinger have, however, been criticized by Hoffmann et al. [30] as well as Aucremanne et al. [16] and Dohring and Mordonu [31], mostly for basing the estimations on arbitrary assumptions. For example, Dohring and Mordonu criticize Brachinger's decision to set the loss aversion exogenous parameter to 2, as it is based on theoretical and not empirical assumptions such as a survey measure or inflation perceptions. Hoffmann et al. challenge each of the premises put forward by Brachinger, among which is a doubt cast on whether the frequency of purchases influences the perception consumers to have on how high the inflation rate is. Different approaches to this thematic are discussed in Chapter 6.

Finding data on purchase frequency of household items is, in any case, somewhat tricky, so estimates leverage the definition of mini (16% of consumption basket) and micro (5% of total consumption) baskets [2].

Demographics is an essential determinant in the context of inflation perception. Inoue et al. [15] have shown that population with lower levels of education are more prone to provide fewer quality data when surveyed. In fact, in their paper [15] it has been proven that for this focus group, it is more accurate to predict inflation rate based on the implicit measure of inflation expectation, meaning their consumption, rather than the explicit one, meaning the survey.

In general, it has been shown in various academic works that different socio-economic cohorts construct different expectations and perceptions about the inflation. Aucremanne [16] argues that the fact that lower-income groups spend proportionally more of their income on necessities explains why this economic cohort exhibits higher inflation expectations than others. A similar pattern applies to the female population since they are presumably more often in charge of daily purchases than the male population. This hypothesis is confirmed by Fluch [2], who found that consumers with a monthly household income of more than 2,900 EUR are more likely to state that increase in prices has occurred.

Bruine [8] and Sabrowski [32] found that there are also certain demographic groups constantly reporting a higher inflation perception. He found those groups being less or no income racial or ethnic minorities, having no college education. Furthermore, Zikmund et al. [33] highlighted the importance of financial planning horizons. They argue that low-income households exhibit a high degree of shortsightedness when it comes to making financial decisions, making them sensitive to price shocks and less informed on long-term price trends. Furthermore, volatility of expectation is often present in such households, due to the lack of certainty on which levels of inflation to expect. Indeed, VanderKlaauw et al. [34] and Linden et al. [35] have demonstrated the higher volatility of inflation expectation among women, individuals without college education, single and lower level of income individuals.

The study performed by Stix [29] in Germany is very indicative on how credible is the official inflation measurement for the general population. They found that 57% of the respondents did not have a positive assessment of inflation rate measurement, raising the question whether such poor trust in official numbers influences inflation perception as such.

Another hypothesis by Malmendier and Nagel [19] indicates the importance of personal experience when forming inflation expectations. They argue that there is a higher value in macroeconomic trends experienced in an individual's lifetime, opposed to available historical data. In the late 1970s, the Chairman of the Federal Reserve Paul Volcker noted that the mid-60s generation that has experienced nothing but inflation, exhibited a different behavior than their more elderly counterparts because the younger generations were skeptical about returning to general price stability. This still seems to hold relevance in the modern economy, as recent macroeconomic trends have more of a weight on younger generations' inflation expectations, whereas the older generation draws their conclusions from a long time span, including even quotes such as the one at the beginning of this chapter.

That quote, along with past experiences and the negative publicity about inflation create a somewhat negative image that the general population has about the topic, without even knowing what inflation is, or what is its significance for the economy. Shiller [7] ran a study on why people dislike inflation, finding that the most common reasons are that it hurts the standard of living, by increasing living costs while keeping the wages at the same level. Furthermore, respondents indicated slowing down growth, or national prestige damage due to devaluing of domestic currency as other reasons.

1.3 Problem statement

The previous section has established that the general population is somewhat prone to having a wrong perception of their consumption patterns and how they are affected by price increases, forming an uninformed user hypothesis which will be used throughout this work. Furthermore, inflation, regardless of the fact that it is an essential macroeconomic performance indicator, has a somewhat unpopular image associated with it. This image, along with the fact that it is directly linked to personal consumption, causes many economic subjects to have a wrong perception on how high the inflation is, and how it is affecting both the economy and their budget.

Chapter 2 is going to showcase the existing personal inflation calculators, their joint aim being producing a personalized inflation curve based on individuals' consumption pattern. The common denominator for most of them is the fact that users need to input their exact consumption in monetary units. This work assumes that the uninformed user does not estimate their consumption patterns correctly, leading to a wrong personalized inflation rate.

1.4 Goal and expected results

Building on this problem statement is the hypothesis that one can estimate a personalized inflation rate of an individual better based on existing consumer expenditure data, i.e., the Austrian Consumption Survey. The idea is to build a profile by asking the uninformed user simple questions to determine necessary information on their consumption. Once the profile is established, user's consumption pattern is estimated relying on the statistical data from the consumer survey.

Therefore, this work will focus on investigating the precision of an alternative approach to personalized inflation estimation, more precisely, the weights associated with individualizing consumption patterns. Since a separate qualitative and quantitative study would be required to compare the output of this approach to the production of the current state of the art personalized inflation calculators, this work will focus on discussing the theoretical fundamentals also taking into consideration the resulting statistical estimation of this method's precision. Therefore, the research question is: "In the context of personalized inflation rates, what is the appropriate algorithm for estimating consumption patterns when the input is provided by uninformed users?"

1.5 Methodological approach

Design Science Methodology, used for purposes of writing this work, is defined as a activity which contributes to understanding a phenomenon, where a part of the phenomenon is created instead of observing it occurring naturally [36]. It is for this reason that the artifact, which is the inflation analysis and personalization tool, will be developed and used to create a part of the phenomenon that will be observed. Moreover, usage of this tool will extend the boundaries of human and organization capabilities [36], augmenting therefore the capabilities of observing the created phenomenon. This phenomenon can hence be observed as feedback on various inputs provided, allowing to perform statistical measures whose goal is to test the hypothesis stated in this work.

For the scope of this work, a visualization and user input framework has been developed, the goal of which is to provide means for users to input variables relevant to their own consumption, and receive feedback on how it influences inflation as a key economic indicator, tailored using those variables. The outcome of constructing and evaluating the model is presented to address the key research question. Tools used to construct and evaluate the models are publicly available Clus [37] and Microsoft Azure [38], mostly because of the exact matching scope of the former, and the previous knowledge obtained during the TU Business Informatics Master program of the latter. The methodological approach will be discussed further in Chapter 3.

1.6 Outline

This work is structured by starting with an initial literature and state of the art review in Chapter 2. In this chapter, the theoretical background is provided on domains relevant for the development of both the thesis topic and artifacts following the elaboration and evaluation. Furthermore, it holds relevance because of the in-depth investigation to state of the art implementations publicly available. Chapter 3 discusses how the research models were developed and evaluated. Chapter 4 elaborates on the technical and usability aspects of the artifacts generated for this thesis, as well as their interdependence when assessing results. Chapter 5 provides the outcome of models' evaluation, as well as the reasoning behind obtaining and explaining the results. This work concludes with Chapter 6, which provides conclusion and discussion on method, outcomes, and possible improvements.

CHAPTER 2

State of the art

This chapter focuses on analyzing the theoretical framework behind this work, to understand its position and possible application within the usability and relevance domains. It consists of three main elements: information visualization, perception of macroeconomics and value of statistics and inflation. The relationship and the size of the scope of these topics are symbolically illustrated in Figure 2.1. Personal inflation is the primary scope of this research is also added to the illustration.

The information visualization section analyzes the history and motivation for data visualization, highlighting its importance for both data analysis and data popularization, as it provides a more comprehensible way of presenting data to a broader audience.

Perception of macroeconomics and value of statistics deals with the acceptance of those two topics among the general public. This section builds on the thesis stated in the problem description in the introductory chapter, namely the false perception that people might have of some key economic indicators, among which is inflation, regarding its image, relevance, and values. Finally, this section investigates into online sources of macroeconomic data in various formats, focusing on sources which are easier to access and comprehend by an average citizen.

Inflation is the part where this work provides a high-level overview of the current state of the art of inflation from a general public viewpoint. With this in mind, this section firstly investigates its state in the macroeconomic framework, examining its recent trend and links to the overall economic situation, with both a global and an Austrian focus. This section drills further down on this topic, nearing this work's research focus by investigating on inflation analysis and visualization tools available to general public, and finally, personal inflation. The latter provides a literature overview on personal inflation, as well as a review on existing personal inflation calculators, along with their usage and scope. Finally, a summary is provided emphasizing the most important points of this chapter.

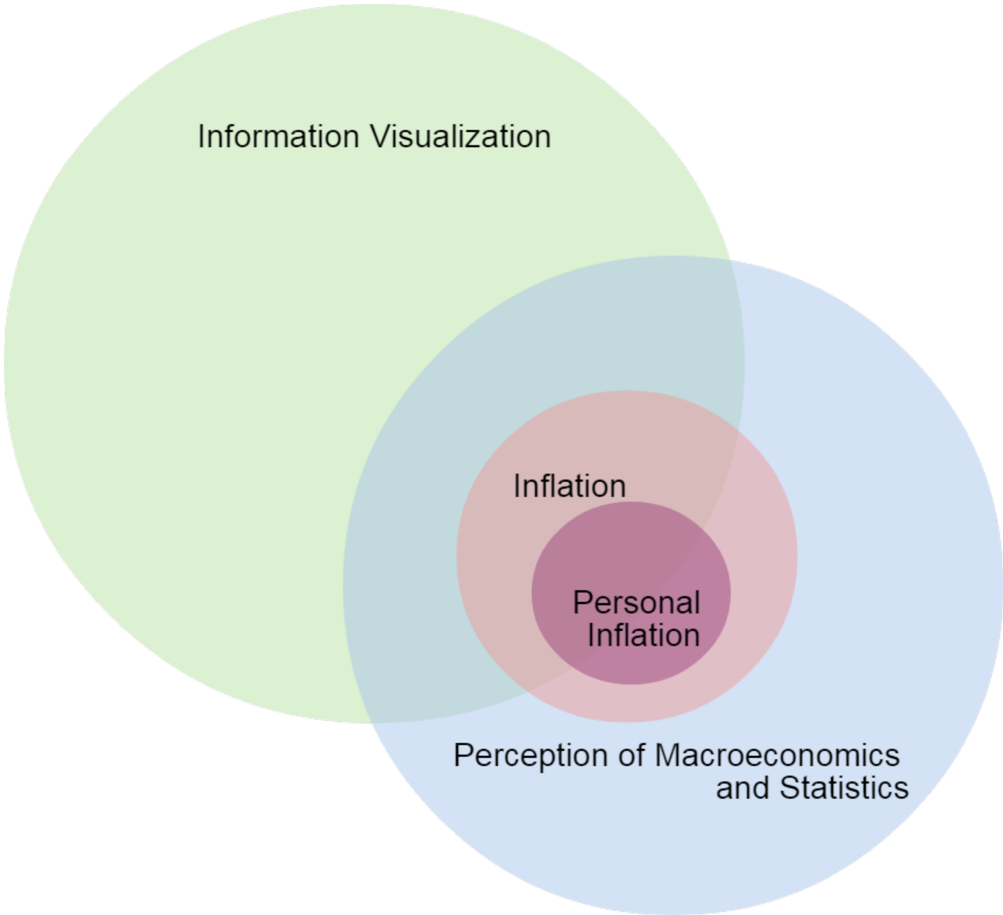


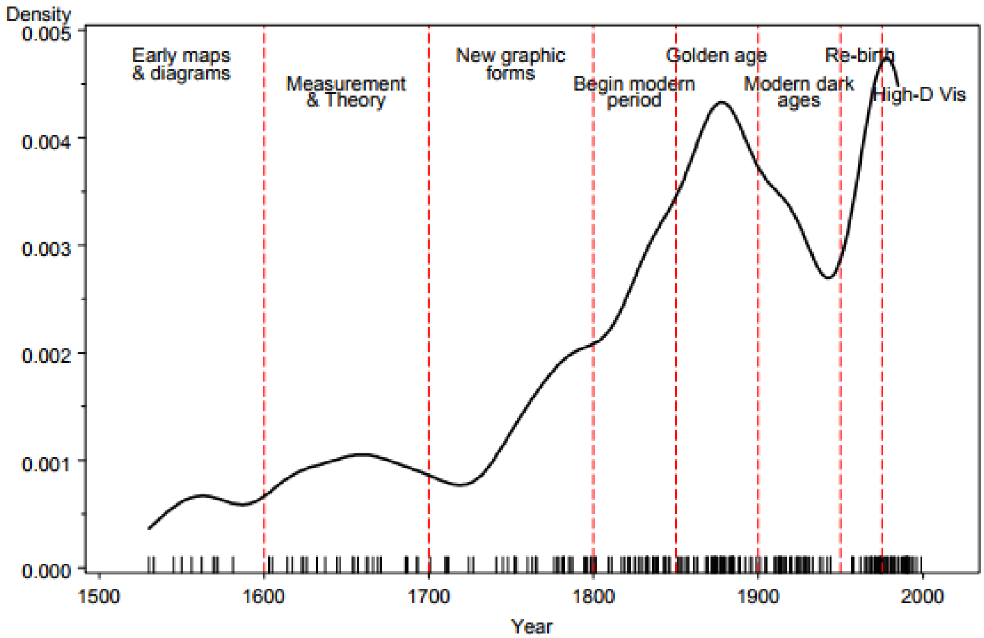
Figure 2.1: Relation of State of the Art research topics - an illustration

2.1 Information visualization

Visualization [39] represents, explores and manipulates data graphically with the scope of providing a deeper insight or an easier understanding of it. In other words, it maps data to a visual form with a goal of supporting human sense-making.

Information visualization (Infovis) has been long used in as an instrument for storytelling [40], although it is common to consider statistical graphics a modern creation.

In his work "A brief history of data visualization", Friendly [41] argues that "the graphic portrayal of quantitative information has deep roots. These roots reach into the histories of the earliest map-making and visual depiction, and later into thematic cartography, statistics and statistical graphics, with applications and innovations in many fields of medicine and science that are often intertwined with each other". Furthermore, he divided the data visualization history into eight epochs, as shown in Figure 2.2;



Source: A brief history of Data Visualization[41]

Figure 2.2: Milestones of data visualization developments

- **Pre-17th Century: Early maps and diagrams** earliest depictions if quantitative information can be found as early as 10th century in the form of a time series graph depicting changing positions of seven most critical astral bodies over time and space [42].
- **1600-1699: Measurement and theory** in the 17th century, the most prominent topic of data visualization was the physical measurement of time, space, and distance. This century, therefore, saw the rise of analytic geometry and coordinate systems, which were practically applied in navigation and territorial expansion. Furthermore, probability theory, as well as population studies have taken off with works of Pascal, Fermat Graunt, and Petty.
- **1700-1799: New graphic forms**. Map making was evolving, from merely showing geographical positions on a map to showcasing additional properties of terrain. This led to the creation of isolines and contours. Mapping of medical and economic data, as well as other abstract data, can be traced to this period as well, building on the lessons learned from geological mapping. Statistics was being refined, as the statistical error was introduced.
- **1800-1850: Beginnings of modern graphics**. Most of the current data display forms were discovered in this period, most notably bar and pie charts, time series plots, histograms, line graphs, contour plots, etc. Cartography evolved by

the creation of thematic maps, which aimed to capture various topics and their implication and presence on a geographical map. These issues included economic, moral, social medical and others; but also captured natural phenomena such as weather tides, etc. In England, however, statisticians still found little use in graphs. Back in those times, statisticians were divided between "table people" and "graph people" with the former creating a formidable majority.

- **1850–1900: The Golden Age of statistical graphics**. The previous period led to late 19th century, in which all conditions for an explosion of usage of graphical visualization methods were set. Official statistical offices were being established throughout Europe, as a reaction to ever increasing the need for planning, commerce, transportation, and industrialization. This phenomenon, in turn, as a side-effect produced data output which led to the need of reducing the complexity of data understanding using data visualization.

- **1900-1950: The modern dark ages**. In this period, the late 19th-century enthusiasm for data visualization has vanquished to be replaced by formal models in social sciences. However, the absence of innovation saw acceptance and standardization, as graphical methods entered all societal pores, including even English textbooks, government, commerce (Gantt and Shewart charts) and science. Furthermore, visual analysis proved crucial for discoveries, such as Maunder's butterfly diagram which leads to the invention that sunspots were reduced in frequency from 1645–1715.

- **1950–1975: Re-birth of data visualization**. Due to computer science research and supporting technology, data visualization was back on the innovation train again. Combined with exploratory data analysis methods, new paradigms were discovered that have shed light on many new areas and lead to growth in visualization methods and techniques. Infovis, as we know it today, was established in this period.

- **1975–present High-D, interactive and dynamic data visualization**. Visualization has grown into a fully developed, interdisciplinary research area; becoming means for predictive analytics as well as distilling the complexity vast amounts of data have nowadays.

Recent trends also support exploratory visual analysis and decision making [43][44]. Savikhin et al. [45] used this technique in their work about demonstrating applicability of visual analysis in decision making in the context of bidding; more precisely analyzing the winner's and loser's curse [46][47][48][49]. Their conclusion was that visual analytic aided the experiment participants in making improved decisions compared to participants that had the information displayed in a tabular form. This illustrated the advantages of using a visual representation of data to overcome the limitations of bounded rationality that arises when a subject cannot grasp the relevance and the overall picture of all the information available. Another major point was the interactivity of visualization. This property allows the user to drill down and slice the data intuitively based on the level of understanding that needs to be obtained. By providing the user with immediate feedback, it has been remarked that this has further increased the level of understanding and the feeling of participation.

Yi et al. [50] states that regardless of the fact that Infovis systems at their core have representation and interaction as two main pillars, the latter is often neglected in implementation and research. Their work focuses on promoting the importance of interaction as an essential part of Infovis; since without interaction the data representation becomes limited and static and is therefore not providing the end user the possibility of interacting with the data to produce a visual that fits best with their understanding. Yi et al. [50] highlight the importance of user interaction operations such as filter (conditional selection), encode (a different representation), reconfigure (a different arrangement), abstract/elaborate (more or less detail) etc.

Correa et al. [51] also point out the component of ambiguity in data visualization and analytics. Their work focused on quantifying and presenting the aggregated results of the uncertainty that is present in the data, due to noise, error or unreliable sources. Aigner et al. [52] stress the importance and role of visual analytics in analyzing time-oriented data, in an attempt to create a framework for systematically choosing the appropriate visualization technique from the vast selection available. Silva and Catarci [53] also focus on temporal data, even stating the primary role of data visualization.

> *"The main purpose of adopting a visual representation in a database system is to communicate clearly to the user the information content of the database, concentrating on essential features and omitting unnecessary detail"*
>
> - Silva and Catarci, *2000*

Furthermore, the importance of interactive timelines, and giving the user the possibility of adjusting and manipulating data, to potentially explore the relationship between historical events was highlighted, similarly to what was expressed in Savikhin et al.[45].

As it is shown in Chapter 4, the Stacked graph was used for visualizing category contribution data for the overall inflation rate. Since the main idea behind a stacked chart is to show much individual time series, and how they add up to a more prominent whole [54], this seemed as an appropriate graph type for the purpose at hand. Byron [54] also pointed out that the most significant issue of these graphs might be legibility, a feature which was not observed on the final versions of this project's diagram; and was partially avoided by using a legend tooltip displaying point values.

The stacked chart was also chosen for its properties as a visually impressive visual style, which, as Moere et al. [55] argues, compels the potentially sizeable audience to engage with the visualization, or share their visualization experience with others. In their work, they have shown the effect and the measurement of the impacts of information visualization on insights that people discover; but also on their perception of determined ideas. They also stressed the influence of style on insight depth, on an example survey among participants that were able to make distinctive differentiation on visuals that did not have a legend associated with it.

Another aspect Byron [54] stressed on was color. Coloring various layers of the stacked graph can prove to be quite challenging, as one should find the optimal balance between encoding information with color and not distracting the viewer too much. At the same time, there should be as much as the possible contrast between the layers, so that the viewer can easily make up between layer borders [54]. In the implementation of the project accompanying this thesis, particular emphasis was put on the coloring of sub-graphs in the stacked chart, respecting the above rules. This is why, in the Main Aggregates to Inflation View, red is chosen as services color, blue is the color of choice for goods, green for food and yellow for energy. Furthermore, since the Contribution of Sub Aggregates to Inflation in Austria graph contains a strict subdivision of the previously mentioned categories, different shades of the colors associated with those categories were used for visualization of that graph. For this reason, communication category is painted in rose, housing in crimson, transport in apple, recreation in currant and miscellaneous in mahogany.

2.2 Perception of macroeconomics and value of statistics

Biens [56] made a point of how many people use statistics in the real world in his research on teaching the relevance of statistics. He states that people are naturally anxious about statistics and having the "I have never been good at math" approach limits them from using statistics to their benefit. To overcome this fear, Biens argues that one needs to focus the individual's attention on the kind of information which is already known or partially perceived by the user.

How does general population benefit from macroeconomic statistics? Bumpstead and Alldritt [57] highlight the role of official statistics in United Kingdom's democratic process, stating that the numbers are crucial to the public understanding of the government, society, and economy. In the discussion on the utility of statistical measurements, they argue that it was initially produced for informing ministers and providing feedback on the policies brought forward. Initially, broader societal value was ignored. It was as late as 2008 that the Statistics and Registration Service Act [58] became law in the UK, its scope and objective being promoting official statistics to serve the public good. This has expanded the user base of these statistics, so, as an additional side-effect of this legislature, the governmental departments creating the statistics had to take the augmented base of users consuming the statistical data into consideration. Singh [59] stresses the importance of statistics as a tool of synthesizing data and presenting them in a tabular, diagrammatic or other forms for easier comprehension. The scope of this process and its proper use is the immense contribution to both the scientific and societal method. Huff [60] takes another view of statistics in his book "How to Lie with Statistics", pointing out the dangers of biased and distorted data and its effects. Wheeler [61] goes deeper and studies the impact of manipulating public opinion in America with the biased interpretation of statistical results, or influences on data collection and analytical measurement applied. These are all arguments showcasing both the power of statistics, but also the anxiety surrounding the interpretation of statistical data by laymen citizens.

This leads to an essential factor in providing this data; its accessibility. Bumpstead and Alldritt [57] argue that information needs to be not only readily accessible to the general public, but it needs to be accompanied by informational context and comment which interprets the data. This allows an average user from the general public to quickly identify the data which is of relevance to them, as well as understand the implications a statistical measure has. In this way, statistics acts as an objective explanation provided to a layman citizen user and a simple way of consuming information coming from different sources.

Moreover, as Blendon et al. [62] showed, there is usually a substantial gap between how the economy is viewed by experts and the general public. Firstly, they state the relevance of personal experience, and the divergence of it from the official data; similarly to what this thesis presents in the problem definition chapter. Furthermore, they note the fact that people often use other sources of obtaining information besides of official governmental statistics, due to the doubt expressed for their accuracy. This, in turn, opens space for manipulation by the media, that tends to portray the economy worse off than it is, stimulating pessimism among the general public. Experts, on the other hand, are more protected from the influence of media or other information outlets, since they are a part of that occupational segment. Hence, this usually leads to higher level of optimism among experts, compared to the general public.

Therefore, the relevance of macroeconomic statistics exhibits itself in its contribution to forming of macroeconomic policies, and the democratic process. Having an impartial measurement of economic vital economic indicators provides means of democratic accountability to bodies steering the public policy measures which influences them. Bumpstead and Alldritt [57] connect the sphere of statistics with the electoral cycle in the UK. In this discussion, an example of 2010 General election is noted, where there was increased media attention to the publication of that quarter's Gross Domestic Product (GDP) since it was published only days before the general election took place. The results of this paper undoubtedly influenced the outcome of the general election, since the interpretation of results has shown that the UK was coming out of recession.

Campbell's [63] and Scanlon's [64] works touch upon the relevance of welfare and well-being and their application on the public policy decisions. The fundamental idea, also highlighted by Denison [65], behind well-being is the satisfaction of own wants and needs; which is directly linked to the freedom of spending disposable income. A crucial element in determining it is the relationship between income and price perception. Just [66] notes that the best way to detect this link is to observe income and consumption decisions at various prices, measuring welfare effects.

This brings the next question: how is the price level perceived by an average citizen?

Janiszewski [67] indicates that behavioral pricing literature agrees that the judgment on the attractiveness of a market price is based on a reference point, as Adaptation-level theory [68] states. An alternative approach to valuing a market price is Volkmann's Range Theory [69], which suggests that people usually act within the boundaries of a low and high cost when evaluating a market price. Hence, their judgment on its attractiveness is a function of its relative location within this range.

2.2.1 Macroeconomic data available to general public

This section will focus on providing a brief overview of sources of macroeconomic data available free of charge on the internet. The scope is to identify websites that are accessible by general public providing up-to-date information on economic critical economic indicators to the user in the form of graphs or tables, with or without providing contextual information. That implies that blogs such as CheapTalk [70] are out of the scope of this state of the art research. Furthermore, the comparison of these websites is also out of scope, as the idea behind researching state of the art is to gather possible inputs for the inflation visualization tool, one of the two artifacts of this thesis. Due to a vast extent of websites falling into this profile, this section will list only a limited selection, providing a short description of their content and scope. Furthermore, sources which have no registered data for Austria will be excluded from state of the art. Finally, research will include providing a quick evaluation of data availability for Austria-related data.

There is a vast number of resources readily accessible to general public, providing macroeconomic data and reports. Organization for Economic Co-Operation and Development (OECD) Key Economic indicators Database [71] is perhaps the most exhaustive one. It provides both monthly forecasts as well as yearly economic surveys; along with a wide selection of data. The data is displayed in a somewhat user-friendly way, for purposes of being consumed by the general public with little or no economic background. Showcased indicators include population, education, GDP, Tax, income inequality, CO2 emissions, debt, and unemployment. More importantly, all data is shown in both trends, for the last six years, and ranking view, which is a comparison to other OECD countries for reference and more natural understanding. OECD's interface also allows the user to view detailed data on topics, which include agriculture, development, economy, education, energy, environment, finance, government, health, innovation and technology, jobs and society. This gives the possibility of viewing data such as fertility rates or road accidents per 1 million inhabitants. All this data is available per country, and data for Austria has the same availability as for the rest, including comparisons to peer countries.

The World Bank [72] economy database contains a selection of economic indicators, accessible via a simple web interface. Data is categorized based on different critical economic indicators. Indicators include Adjusted net savings, including particulate emission damage (% of GNI), Agriculture, value added (% of GDP), Central government debt, total (% of GDP), Exports of goods and services (% of GDP), External debt stocks, total (DOD, current US$), Foreign direct investment, net inflows (BoP, current US$), GDP (current US$), GDP growth (annual %), GDP per capita (current US$), GDP per capita growth (annual %), Gross savings (% of GDP), Imports of goods and services (% of GDP), Inflation, consumer prices (annual %), Total reserves (includes gold, current US$) and others on a yearly time basis. Furthermore, a Database viewer tool [73] is provided, allowing the user to customize data visualization in forms of line charts and maps for various critical economic indicators. The usual data range is from the 1960s, depending on the index. Austrian data is represented in multiple data ranges; so for instance, Expense is served from 1972, and charges for the use of intellectual property are described from 2005. Specific indicators are not represented for Austria, such as External debt stocks, Grants, Net ODA, as well as short-term debt.

The Economist [74] has a rather simple data interface, the goal of which is to provide a compact overview of key economic indicators in the form of two tables. The first table deals with output, prices, and unemployment; covering GDP, Industrial production, Consumer prices and unemployment rate. The second table concerns trade, exchange rates, interest rates and budget balances, and encompasses trade balance, current-account balance, currency units, budget balance and interest rates. All data is represented for the last year or on a year-on-year basis, in line with the compact nature of this interface. Austrian data is represented among 56 countries and entities listed. The Economist furthermore provides other visualizations, such as the Big Mac Index [75], House Price Index [76] and a geographic overview of European critical economic indicators [77]. It is also important to note here that The Economist has limited access to non-members, which might create a barrier for the general public to access and view the data.

International Monetary Fund (IMF) [78] provides access to various financial indicators, such as Global housing watch, Coordinated direct investment survey, International Financial Statistics and others. Furthermore, it is possible to access the World Economic Outlook Databases, containing selected macroeconomic data from the biyearly World Economic outlook report. This database can be used to download data on inflation, unemployment rates, the balance of payments, fiscal indicators, commodity prices, etc. from the 1980s until two-year future projections. United States Department of Agriculture (USDA) [79] hosts a historical and projected data set for 189 countries. This dataset contains information on GDP, population, real exchange rates and inflation from 1969 until expected 2030. Both IMF and USDA provide representative data on Austria.

European Data portal [80] provides open data on European public sector information. The portal allows the user to browse datasets by categories, including agriculture, fisheries, forestry and foods; energy, regions and cities, transport, economy and finance, international issues, government and public sector, justice, legal system etc. The interesting part of this portal is its diagnostic on open data quality, impact and portal maturity per category and country. With this in mind, it is interesting to observe that Austria is above average in all three groups on which the open data is valued in the portal; Readiness-policy of public data, Readiness-impact of open data and portal maturity.

The statistical data warehouse of the European Central Bank gives the possibility of visualizing a set of indicators for the Euro Area, including Inflation rate, Monetary aggregate M3, GDP, population, unemployment rate and others. Data can be expanded for viewing in more detail, and other datasets can be selected; such as Shipment of Euro banknotes statistics, Balance sheet items, Bank lending survey statistics, etc. This data source would be more appropriate for experts due to its specialized nature. Austrian data are not separated from Euro Area.

Eurostat [81] provides databases and tables by themes, such as general and regional statistics, economy and finance, transport, etc. Tables on EU policy and cross-cutting topics such as quality of life, migrant integration indicator, equality, quality of employment and other are provided as well. Eurostat's database provides a method of visualizing and downloading data in the form of bulk and web service download and is used as a primary data source for this thesis' artifact as well. Austrian Data is well represented within the macroeconomic data sets.

European University Institute [82] provides a collection of other micro- and macroeconomic data repositories from various sources, along with a short meta description of data and means of accessing the repository and obtaining the data. Following are examples of macroeconomic data in EUI's collection.

- **Banking Data: SNL Financial** - provides data on 29,000 banking institutions worldwide
- **Central And Eastern European Data** - Economic data on Central and Eastern Europe, from 1990 until 2017. provided by Vienna Institute for International Economic Studies
- **re3data Registry of Data Repositories** - Global registry of research data repositories, provided by Humboldt University, Berlin
- **Datastream** - global macroeconomic and financial data platform. Contains key economic indicators for 175 countries and 60 markets, maintained by Thomson Reuters
- **Demographic Yearbook** - yearly data on demographic indicators such as age, sex, birth rates, mortality and others, for countries in the United Nations (UN).
- **Electoral and Parliamentary Data** - database on Ideology, Money in Politics and Elections (DIME) includes a vast database of records for political contributions. Developed at Stanford University.
- **ECMI data on capital markets** - comparative statistics on European markets, structured in primary sections based on market type.
- **European Central Bank data** - data on activities entailed in the European Central Bank. Data such as Policy and exchange rates, money, credit and banking, ECB surveys and payment statistics are part of this datastream.

- **Global Financial Data** - long range financial data for bills, stocks bonds and other instruments.
- **Federal Reserve Economic Data** - data collected by Federal Reserve Bank in St. Louis is grouped and presented in thematic categories; Academic data, National Accounts, Production and business activity, prices, International and regional data.
- **International Trade Centre data** - on market access, foreign direct investment and global trade, provided by ITC in Geneva.

2.3 Inflation

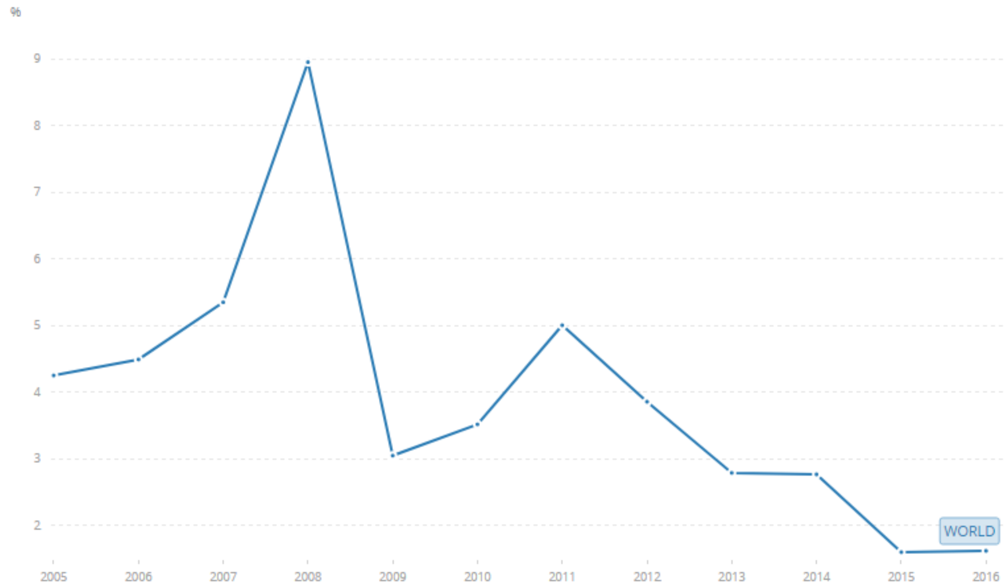
This section will firstly focus on providing a current global outlook on inflation, building upon its relevance as elaborated in Chapter 1. Secondly, the current state of the art in inflation tools and knowledge available to the general public will be analyzed. Thirdly, an analysis of personal inflation will be provided, initially by providing a literature overview on what personal inflation as a concept entails and what its state of the art is, and finally by providing a general overview on the tools available for calculating personal inflation rates.

2.3.1 State of inflation

Although the world economy has been battling with issues other than inflation over the last years, everybody knows inflation is bad. Past stories of hyperinflation still lurk in the conscious of the general public, and news about inflation rising are usually not welcome. Central banks have, willingly or unwillingly, done an excellent job at maintaining inflation at bay over the last couple of years, so the inflation scare seems to be a thing of the past.

Is inflation actually all that bad, and if so, are there reasons to worry about it? Boyd [83] argues that even moderate inflation with rates as low as 5 to 10 percent can hamper growth. Boyd explains that inflation means that the interest rates will be going down, and people are less inclined to save because of it. That means that people will tend to invest, and every investment needs a loan from the bank. The banking sector will then have an influx of borrowers, which might be of dubious quality, which will lead to the bank not being able to tell good from bad borrowers. Banking sector reacts to this by charging a higher interest fee, which will reduce the number of investments, as low-risk investors will be forced out of the market. Less investment means less growth and general slowing down of the entire economy. Baharumshah [84], Krause [85], and Cecchetti and Krause [86] investigated the relationship between variable output, inflation and economic growth. They found that variable output, caused by economic instability, tends to increase inflation rate, and, similarly to Boyd, they found that inflation rate hurts economic growth.

Boyd [83] concludes that, although world economy has not seen a dramatic increase of inflation in decades, inflation is still a lurking threat, also because it is tough to fine



Source: World Bank

Figure 2.3: World: Inflation Development between 2005 and 2016

tune and find the thin line of the inflation rate which benefits growth, without hampering it. Boyd closes his work with the assumption that pinning down this inflation target is the duty of individual countries.

Fine tuning the inflation rate, however, has proven itself as a somewhat challenging task over the past couple of years. Duffey [87] highlights in his work the importance of learning process, which has occurred over the past couple of years both from the FED and also the society, regulators and financial markets. This effect has, as he argues, led to FED controlling the inflation rate and meeting inflation targets over the last years better than the immediate years after the great recession.

As Murphy [88] argues, according to standard economic models the US should have experienced a period of deflation during the Great Recession years of 2007 to 2009. This has, however not happened, as prices continued to grow even during those years when the economy was halted [89]. Moreover, in the recent recovery years, experts expected inflation to pick up, as growth was recorded and labor markets tightened since unemployment was in the fall. Even then, their predictions have fallen short, since inflation stayed at low levels, and FED missed out on their inflation target.

These examples showcase issues with current inflation forecasting models, which are based on Phillips curve, and have ever so well performed until the Great Recession. The failure of these models creates an uncertain ground for economists, looking to meet their inflation forecasts and also prevents policymakers to make optimal decisions.

Ball and Mazumder [90] found that accelerationist Phillips curve needs to be modified to include weighted median of price changes and allowing the slope of the curve to change with the variance and level of inflation; and also concludes that due to inflation expectation anchoring in the United States, which is set to 2.5 percent, US is likely to avoid deflation in the future, given that the anchor persists.

Murphy provides a similar explanation why inflation is not following the rules set in the Phillips curve; arguing that the expectations have changed. Since FED is committed to a positive inflation rate, this anchors expectations about future inflation. He [91] expands the reasoning for the departure from standard Phillips curve with the unemployment rate, and argues that short-term unemployment rate should be included in the calculations instead of the overall one since it moved up less during the Great Recession and declined shortly after, so less movement in inflation would be predicted. Finally, another factor to consider is the regional economic situation and the price and information stickiness associated with it [88]. Multinational companies having outlets in various countries tend to have slightly sticky prices, basing their information on the overall situation, rather than the local economic happenings, leading to variations between inflation forecasts and the actual state. Coibion and Gorodnichenko [89] also point out the relationship between households and their consumption of gas and their not adjusted inflation expectations. In combination with rising oil prices, and the assumption that firms have similar aspirations as households, they argue that the absence of deflation can be attributed to "good luck" of oil prices rising at the same time as the Great Recession occurring.

Inflation in Austria is categorized by 4 main periods [92]: the pre-World War I period with the relative stability, the World War I period and the hyperinflation that followed it, then the post World War I currency reformed and the Great Depression, followed by World War II and the postwar currency reform and inflation, then the later postwar period including the demise of Bretton Woods system, as well as Austria's membership in Economic and Monetary Union. The exciting point binding all that times together was the overall strategy of the Austrian central bank, which in its 200-year history practiced the policy of stable money and its intention to ensure it. This is also the reason why Austria did not experience significant inflation variances apart from when it was imposed by extreme outside factors such as the two World Wars [92].

Measuring inflation has evolved throughout the years in Austria. Fluch [3] states that consumer price indices have existed in Austria since 1800, and it has progressed sharply from the first calculations to the complex criteria determining the level of inflation in Austria today. Firstly, the number of items included in the consumer's basket has increased from 20 to around 800 pieces. Secondly, the number of price reports for those items has risen from 100 to over 40,000 in 2016. The basket correction now takes place on a yearly basis, as new methods are emerging to fight measurement inaccuracies.

Fluch [3] also mentions an important point which is the consumers themselves. Historical analysis has shown that an average Austrian consumer has switched its consumption preferences away from necessities - Austrian households nowadays are spending less than a quarter of their disposable income on necessities. This is attributed to an overall growth of the economy which has led to a higher disposable income and

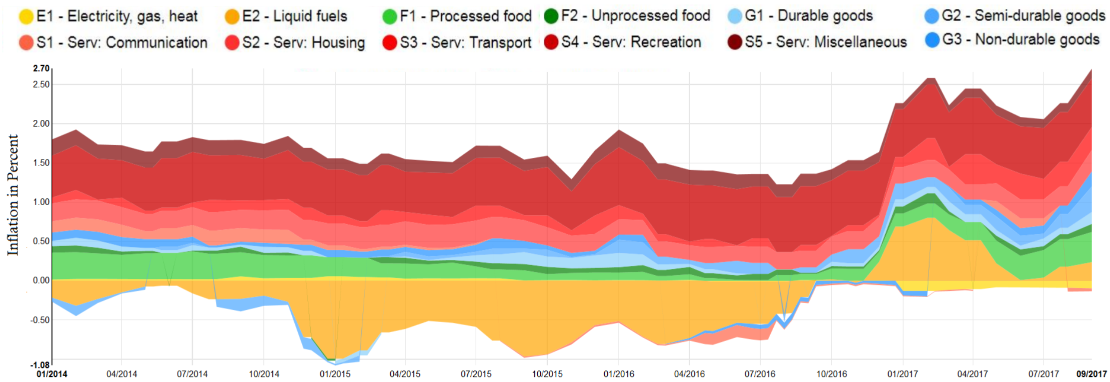


Figure 2.4: Inflation rate for Austria, divided into 12 COICOP categories

has therefore reshaped the consumption pattern of Austrian citizens; a point argued in Chapter 1.

Figure 2.4 illustrates the state of inflation in Austria since January 2014. The categorical division of expenditure categories, which is related to the 12 COICOP categories, indicates that the primary driver of deflation were energy associated categories - i.e., electricity, gas, heat and liquid fuels. This paradigm has, however, changed to an extent in late 2016, as the prices of liquid fuels increased.

2.3.2 Inflation analysis and visualization available to general public

Most of the websites listed in section "Macroeconomic data available to general public" also include inflation as one of most prominent Key Economic Indicators. An analysis performed on those sites concludes that they focus on providing data on either only the overall Consumer Price Index inflation or individual first-level categories that make up the inflation rate. Research performed [74][72][71][81][80] as part of this work did not find similar inflation analysis as provided by this work, where stacked graph visualization was used as means of illustrating the components that make up the entire inflation rate, and how they contribute to it.

An exciting visualization tool that does use concepts similar to the artifact of this thesis is found on the website of the Statistical Office of New Zealand [93]. The graph shows a breakdown of the average consumption basket into 10 categories: recreation and culture, education, miscellaneous goods and services, food, alcoholic beverages and tobacco, clothing and footwear, housing and household utilities, household content and services, transport, health and communication, using a pie chart to illustrate the share of consumption of each of those categories. Additionally, this is a pie chart where each slice representing categories is of different radius, which shows the dynamic of inflation for that particular group.

Furthermore, there is a number of online resources [94][95][96][97][98] explaining the dynamics and value of considering inflation as an important key economic indicator. The state of art research for this article, however, did not come across a dedicated inflation visualization tool or platform that visually decomposes inflation to its forming elements.

2.3.3 Personal inflation

This section will firstly provide a literature overview on personal inflation state of the art, and secondly, it will list and discuss existing personal inflation calculators available to general public.

Literature overview

As O'Donoghue [99] states, there are no two individuals that have the same consumption for all items which are included in the measurement of the overall inflation rate. This has led some researchers to look into ways of finding out the consumption patterns of an individual, in an attempt to estimate a personalized inflation rate based on the individual's consumption, rather than the consumption of an average citizen, on which the national inflation rate is based. Powell [23] used personal estimations of each for his work of implementing a personal inflation calculator. These estimates were mainly relying on individual's ability to estimate own consumption for micro and macro baskets; whereas particular calculations were used for more infrequent expenditure, such as housing and motor vehicle. This is an essential part of personal inflation estimation, as rare purchases such as housing and motor vehicles are more difficult to estimate than frequent purchases, only because individuals do not have to perform those payments as often and are therefore less inclined to know the exact amount spent on those purchases.

O'Donoghue [99] used special techniques for those calculations. For housing, namely, individuals were asked to input the value of their outstanding mortgage, so that average amount of outstanding debt and average interest could be calculated to estimate the overall payment. Furthermore, as inflation rate includes maintenance of the property, one would need to include these costs in the personal inflation rate estimation, especially because they might be significant. Since these costs are very complex to estimate by individuals, the approach of inquiring individuals about the estimated value of their house and area of a country where they live was taken. This data was then combined with information on average property prices by region and calculate an estimation of depreciation rate and its relevance in the expenditure pattern.

Estimating vehicle expenditure is another major problem, as it is difficult to predict whether an individual or household will or will not acquire a vehicle shortly. Seeing that this might have a significant influence on an expenditure of an individual, the approach taken is to detect whether an individual has reported any spending on petrol and oil. If this is the case, the individual is said as a purchaser with interest in vehicle prices; if not their consumption is set to 0. If the individual has been singled out as one that is interested in vehicle purchases, vehicle expenses assigned to them are proportional to the overall expenditure; meaning that the more the individual would spend overall, the more significant their vehicle expenditure would be.

O'Donoghue [99] further argues that the calculator's usage can be in the domain of investigating the sensitivity of the average inflation rate to various consumption patterns, and goes to show in a series of examples of different consumption profiles how inflation experienced might be bigger or smaller.

Kostadinov et al. [100] also highlight the importance the usage of a published personal inflation calculator has on the measurement of official inflation rate; as they speculated that information obtained with such calculator would provide a valuable source of information on possible modifications of inflation rate measurement. Furthermore, a more in-depth analysis of measurement of inflation according to groups, subgroups, and products could be achieved by obtaining such information.

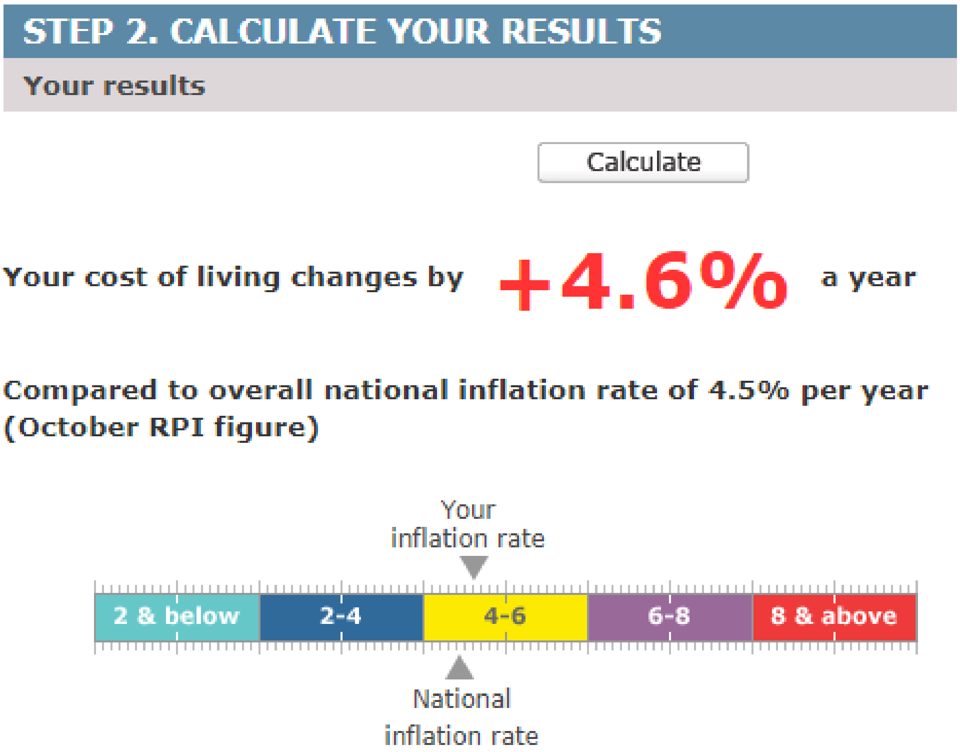
Existing personal inflation calculators

This section will present a selection of personal inflation calculators available to general public. Since this research found that there is a large number of personal inflation calculators, this paper will present only some most prominent ones due to their popularity, relevance for this thesis or unique way of gathering data from the user.

Perhaps the most prominent personal inflation calculator was implemented by the English Office for National Statistics [101], based on O'Donoghue and Powell's work [23]. The basic concept underlying this tool is the monthly personal expenditure estimation by the user, which is inputted through a web interface and fed into the system. The personal calculator then produces a new index for the overall price level based on the coded expenditure pattern. The change in the new price index is used to estimate the personal inflation rate. Note that the costs inputted are not the same across the full spectrum of purchases, and the tool makes a distinction between frequent purchases, such as food, and infrequent such as vehicles, where a cost required is the one over the past years.

Data input is composed of firstly filling in data for monthly spending - food, meals out, alcohol, tobacco, phone charges, clothing and footwear, fuel for transport, heating and lighting, rail and bus fares, child care services, chemists goods and other expenditure. There is a brief explanation as to what each of these categories entails. Secondly, the user needs to input their spending on an annual basis for council tax, house insurance and water, housing repairs, vehicle repair, vehicle tax and insurance, UK and foreign holidays and airfares, furnishing and electrical goods. Finally, the user needs to input their housing costs; that is the value of the property (if owner), outstanding mortgage, rent and living location. Finally, the user can generate their inflation estimation with a click of a button, as seen in Figure 2.5

The calculator has generated significant interest in media and the general public, and it is reported to have reached over 100,000 views on the day of its launch [11].



Source: Office for National Statistics UK

Figure 2.5: Office for National Statistics Personal Inflation Calculator

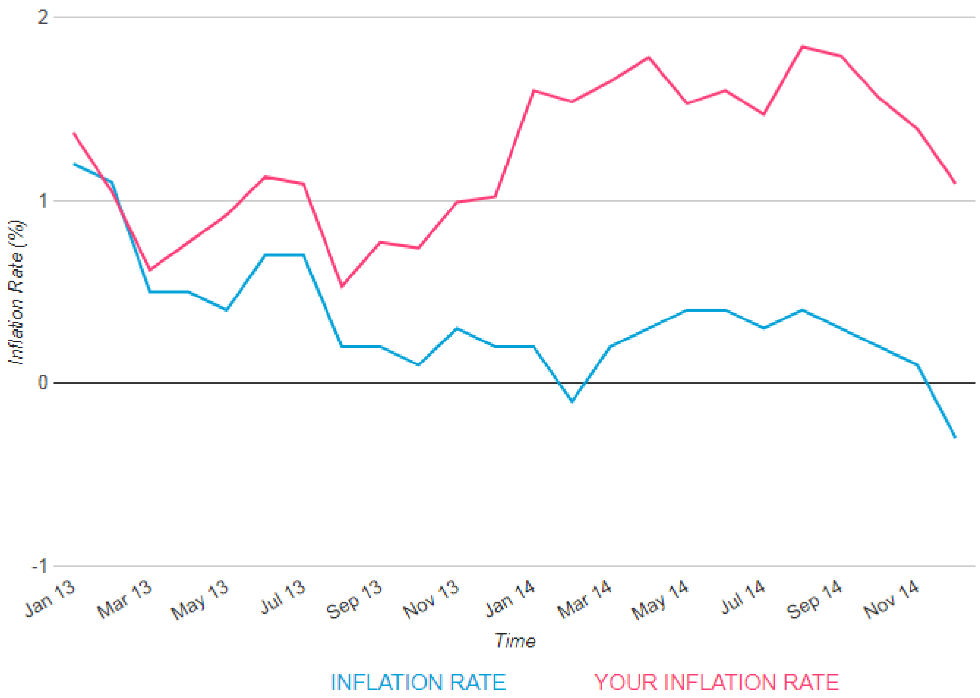
Public Policy Ireland[102] created a personal inflation calculator that is very similar to the one presented in this paper. This calculator bases user input on eight questions rather than relying on the user to input their expenses in numbers, to provide an approximation of a household inflation rate. Those questions reflect the consumption choices that have a relatively significant impact on the inflation rate. Therefore, the author decided to opt for simplicity instead of drilling down to the smallest consumption choice [103]. This is a trade-off between simplicity and accuracy, since asking more questions would improve precision, but at the expense of asking the user to input a lot of information, which might decrease participation rate.

The questions asked are the following, multiple answers can be provided where applicable:

- **Where do you live?** - the offered answers are:
  - Own home, with mortgage
  - Own home without mortgage
  - Rent privately

  - Rent from local authority

- **Do you own a car?** - the offered answers are:
  - Yes, petrol
  - Yes, diesel
  - No
- **What public transport do you use?** - the offered answers are:
  - Train
  - Bus
  - Taxi
  - None
- **Are you vegetarian?** - the offered answers are:
  - Yes
  - No
- **Do you smoke?** - the offered answers are:
  - Yes
  - No
- **Which of the following do you drink?** - the offered answers are :
  - Beer
  - Wine
  - Spirits
  - None
- **Is there anyone in your household engaged in any of the following forms of education?** - the offered answers are:
  - Primary or pre-primary
  - Secondary
  - Third level
  - Other
  - None
- **Which of the following types of insurance do you pay?** - the offered answers are:



Source: Public Policy Ireland

Figure 2.6: Public Policy Ireland: Personal Inflation Calculator

- Home
- Health
- Motor
- None

Personal Inflation Calculator [104] offered by the Dutch Central Statistics Bureau Relies on numeric data input from the user and is in many ways similar to UK's ONS calculator. It divided the spending in 4 categories: Monthly expenditures with items such as food, clothing and car fuel, annual expenditure with things like car insurance, spending abroad and child care, spending in the last five years on audiovisual equipment and computers as well as furnishings and household appliances, and finally, value amounts - where purchase value of new or used car, as well as value of own home, are inputted by the user. Interesting to note here is the presence of default values when the calculator is loaded, which suggests to the user what the average expenditure for those categories is; risking maybe also bias when those values are inputted because of the default effect [105].

Freefincal's [106] personal inflation calculator is attractive because of its simplicity - it requires only three inputs by the user. The first question relates to the number of years the user can estimate their expenses. Secondly, a rough estimation of yearly costs is required for essential items for those years; and thirdly, current annual expenditures for the same necessary things is needed. The estimate is therefore based on user's sole discretion and does not take into consideration variable income or consumption habits the user might have developed in the time panel in question.

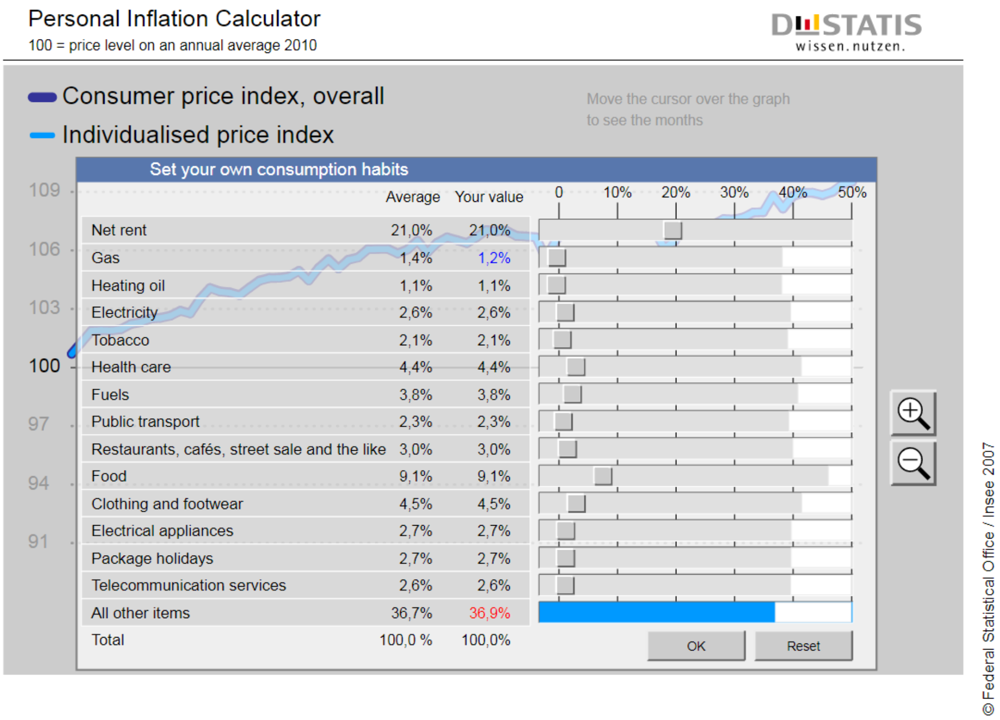
Umass Boston [107] a financial services forum also relies on users' precision in estimating their expenses. Additionally, it inquires over last year's household annual income, current year's annual household income and last year monthly household expenditure. Consumption is not divided into categories, and the user is asked to provide input on expenditure across the entire consumption spectrum; meaning that numbers needed are for Food and Beverages, Housing, Utilities, Apparel, Transportation, Communication, Medial Care, Recreation, Education and Other goods and services. It is valuable to note here that just like in Dutch Central Statistics Bureau's calculator, default values are present, risking the occurrence of the default effect [105].

German Statistical Office - Destatis's [108] personal inflation calculator relies on percentage. In an attempt to abstract the user from numbers, the creators of this personal inflation calculator adopted the approach of inquiring the user to assign a percentile value to their expenses, to determine their consumption pattern. Categories of expenditure are not divided into categories, and just like Umass Boston's and Dutch Central Statistics Bureau's calculators, provides a default value for each category. Categories and layout can be seen in Figure 2.8.

Statistics South Africa also developed a very detailed personal inflation calculator [109]. The consumption inputs are divided into six categories; the first of which is an estimation of monthly expenditure on regularly purchased items. This evaluation should then be shared onto items of the second group, which asks the user to provide an assessment on daily purchases, such as tobacco, food, meals, alcoholic beverages, etc. The third category inquires about calculated other monthly expenditure, which is the base for a total monthly cost. Next class focuses on accommodation expenses, more precisely the value of one's property or rent expenses if the user does not own property. Next category requires input on annual spending on household and vehicle repairs, and finally, the last group inquires on expenditures in previous three years on furnishings and Electrical Goods, Motor vehicles and Telecommunication equipment.

Finally, Austrian statistical office Statistik Austria [110] also provides a personal inflation calculator which is interesting because it gives the possibility of using the simple or more detailed version. The user needs to input data for 15 consumption categories along with motor vehicle expenditure. To further refine their consumption pattern estimation, users can expand each of these groups into subcategories, where an estimate of classes expenses can be redistributed to the two underlying subcategories. So for example, for category Travel, one can specify how expenditure is distributed within this category - whether on Flights, Hotel packages or Accommodation services. This calculator also provides default values for both groups and subcategories of each expenditure.

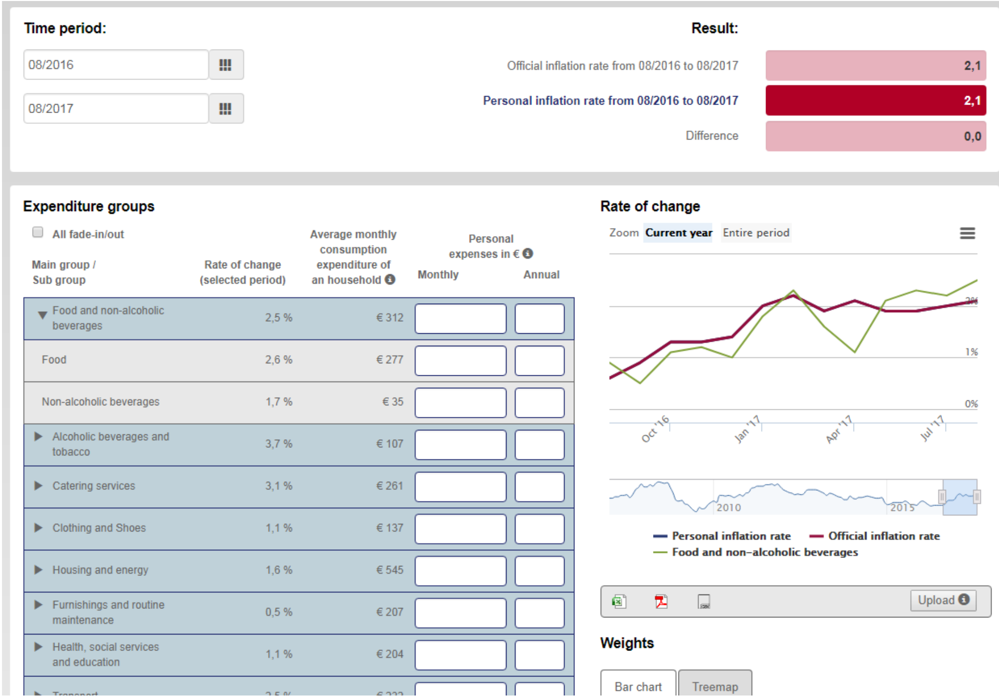
Other tools such as United Arab Emirates Statistics Centre's [111] or Georgia Statistics



Source: Destatis - Statistisches Bundesamt

Figure 2.7: Destatis - Statistisches Bundesamt: Personal Inflation Calculator

Office's [112] use methods similar to previously mentioned.



Source: Statistik Austria

Figure 2.8: Statistik Austria: Personal Inflation Calculator

2.4 Summary

This chapter has provided an overview of both the general topics related to the research focus as well as its state of the art. An essential concept of this work is information visualization, and this chapter has showcased its importance in data presentation and popularization; both dimensions of interest for this thesis. Popularization is of particular interest for crucial macroeconomic actors who are the people themselves. Perception of macroeconomics is a relevant topic which is present in all societal pores, and as such is of high importance to present trustworthy data in a way that its interpretation does not require an economic background. Inflation, as one of the most prominent critical economic indicators, is therefore also relevant; however, it does not seem to capture that high of importance to have a high number of dedicated tools focused only on visualizing or providing inflation data visualization.

This research has also shown that there are some personal inflation calculators available to the general public, confirming the topic relevance for both scientific and popular sphere. As opposed to the concept laid out in this work, most of these inflation calculators expect a correct expenditure input from the user. Furthermore, the personal inflation calculation presented does not contain categorical information; i.e., the user does not have feedback as to what the exact cause of the higher (or lower) personal inflation compared to the national level is. Finally, the most similar tool to the artifact concept of this work presents a series of 8 fixed questions to the user, from which it derives its estimation; again solely on the overall personal inflation rate and not divided into contributing category. This is a simplification of the underlying model presented in this work, as questions are not fixed up-front and are interdependent based on the previous answer due to the decision trees modeling conditioning their creation. These factors strengthen the innovative element of this work, as a tool with the same functionality as the artifact of this work is currently not available to the general public.

CHAPTER 3

Method

"There are three kinds of lies: lies, damned lies, and statistics"

- Benjamin Disraeli, *1891*

This chapter focuses on describing the research method chosen to meet the objectives of this work, addressing the concept, requirements and development method. Moreover, this chapter will provide insights on the empirical study which led to the evaluation and discussion of this thesis.

3.1 Methodological approach

This work relies on the Design science paradigm [113], the scope of which is designing an artifact for problem investigation and understanding. The proactive paradigm is composed of seven main guidelines:

1. **Design as an artifact** - The result is stated as a creation of an IT artifact which supports the analysis of an essential organizational problem. Compared to the earlier works [114][115] Hevner et al. [113] both widen the definition of an IT artifact, by including additional models, constructs, and methods, and also narrow it down in the sense that elements of organizations and people are not added. Finally, in the context of this thesis, it is important to note that, according to this definition, artifacts designed for the purpose of design science are rarely fully elaborated systems, and as such do not necessarily have to be used in practice. Their sole purpose is the construction of models or representations of the model domain, for the scope of resolving the research problem at hand. Finally, the argumentation for this guideline goes along the lines of demonstration of the feasibility of the design process and product.

2. **Problem relevance** - The general objective of research in information systems is to obtain understanding and knowledge, enabling the implementation of information systems for resolving business problems. Unlike behavioral science, whose main aim is to observe natural patterns, thus constructing theories to explain the underlying paradigm, design science constructs innovative artifacts that can change the patterns, observing and reporting on their occurrence.

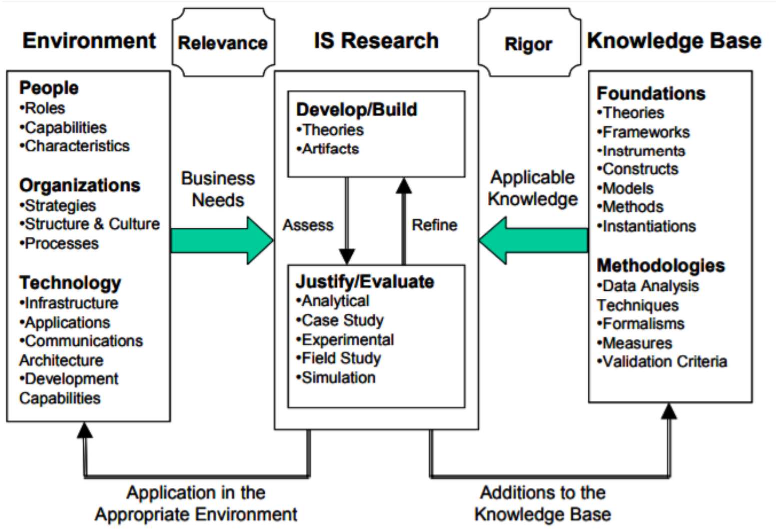
3. **Design evaluation** - Key performance indicators, such as quality, efficacy, and utility of a design science system must be demonstrated to argue its usability in the research process. Evaluation is an important step in the research because it establishes parameters of theory evaluation, as well as the validity of the scientific approach. A designed artifact is valid and effective when it operates under validity constraints of the problem it was meant to solve.

4. **Research contributions** - Essentially, design science research must answer a core question: "What are the new and interesting contributions?". Contribution to areas of design artifact, design construction knowledge, and design evaluation knowledge is a mandatory requirement for performing design science research. In fact, such a research holds potential for three types of research contributions:

    - Methodologies: regarding evaluation, analytic and observational methods
    - Foundations: the creative development process of methods, models and other constructs essential for the research itself
    - The Design Artifact: finally, the design artifact itself can be a valuable contribution to the research community and problem-solving process in general.

5. **Research rigor** - this guideline addresses the adherence to a strictly defined set of rules for data collection and analysis. As opposed to mathematical formulation and modeling, information science artifact modeling might not obey the research rigor existing in those spheres of research. This is why it is advised that an optimal balance should be found between underestimating the research rigor, and not overestimating it in order not to lessen the relevance of the research study. In the context of artifact in the design science process, it is of crucial relevance to understanding why an artifact works, or does not, to be able to reproduce the creation of new artifacts which explore the role and functionality of the latter.

6. **Design as a search process** - essentially, the design is a search for an effective way of solving a problem. Factors between which a research operates must be represented in the design science artifact, most notably the means, laws, and ends. Means represent the constructs and actions necessary to resolve a problem; laws are the forces of the environment and ends are the solutions with their constraints. Design science usually operates in the constrained set of these parameters, in an attempt to resolve sub-problems, eventually combining them to provide the resolution to the overall problematic.



Source: Design Science in Information Systems Research [113]

Figure 3.1: Information Systems Research Framework

7. **Communication of research** - solutions brought forward by design science research must be presented to both technology-oriented, as well as management-oriented audiences. The present method differs for those audiences, as the former is focused on the applicability and feasibility of the solution in their business context, whereas the latter is interested in the feasibility of the construction of the design science artifact at hand. The level of detail in the individual presentations should stay consistent with these goals.

These guidelines were followed during the implementation of this research. Guideline 1 was followed using implementing a personal inflation calculator and inflation visualization tools. Guideline 2 focuses on the relevance of this topic, which is both the educative one about inflation, but more notably, the creation of artifacts which enable both researchers and the general population to analyze their consumption patterns, putting them in the context of general price changing. The relevance of this information is reflected in the analysis of the price trends of items in personal consumption basket, in the scope of eventually modifying own consumption patterns to fine-tune the expenditure of disposable income. Guideline 3 was implemented in evaluating the constructed models and discussing the validity of their application. Guideline 4 follows along these lines, as a new method to approach the personalized inflation information has scientific relevance, and the design artifact is a valuable contribution to the problem-solving process and research community. Guideline 5 was respected with the iterative development cycle of both model and artifact construction, as the application of generating/test cycles ensured the validity of those constructs. Guideline 6 was deployed in the creation of underlying statistical models, as their construction was used to yield an answer to the central questions on factors contributing to inflation variance. Finally, guideline 7 was followed in the creation of accompanying documentation and reports, which are oriented to both management and technical audiences.

Additionally, methods chosen for developing this work are composed of 4 main pillars [116][117]: Requirements gathering, Design, Development, and Evaluation. These methods were the underlying principle behind delivering this work from its conception until the finalization of its results and conclusion.

Reaching the expected goal of obtaining and evaluating a model for predicting an expenditure class followed the following steps:

1. **Literature research** - this phase comprised of researching state of the art on topics such as expenditure perception, perception of macroeconomics and its critical indicators among which is also inflation. The essential part of this phase was establishing a theoretical background acting as a foundation for the later creation of artifacts and models.
2. **Artifact state of the art research** - a relevant part of the implementation of artifacts is researching similar applications available to the general public. The scope of this study is to determine both the innovative relevance, as well as building upon concepts behind state of the art implementations for the new artifact.
3. **Implementation of Inflation visualization and Personal inflation calculator** - this phase focuses on implementing the artifacts, and the underlying models leading to its creation and evaluation.
4. **Artifact evaluation** - evaluating the Personal inflation calculator focuses on assessing the models which enable its creation. The assessment of these models is done in absolute terms, due to the lack of availability of comparative models.

3.2 Artifact concepts

The primary task when conceptualizing both the artifacts of both Inflation data visualization and Personal inflation calculator was to specify the applicability, and the relevance of the artifacts developed. The artifacts, as well as the theoretical framework around which the artifacts are built, have been developed in collaboration with Dr. Koch from the Institute for Advanced Studies (IHS) in Vienna. Because of this fact, it has been established that the primary role and artifact relevance is to support research at the Macroeconomic and Public Finance group of IHS, most notably on inflation analysis and forecasting as part of Austrian Economy forecast [118]. Moreover, it is speculated that both artifacts could have an educational effect for the general public for the scope of raising awareness on inflation as a key economic indicator as well as improving its image [119][7]. Finally, it is expected that the Personal inflation calculator could be beneficial to the general public regarding planning own consumption and spending horizons in the context of price dynamics.

3.2.1 Key requirements

Key requirements were formulated before proceeding with the implementation of both artifacts:

- **Simplification** - this requirement applies to both artifacts. During the analysis of state of the art, it has been noticed that most key economic indicator visualization tools available to the general public do not visualize information for the general public to understand intuitively. This pattern has led to this requirement for the Inflation data visualization tool. On the other hand, most Personal inflation calculators require exact numeric input from the user, and one of the cornerstones of this thesis is that on average, general public is not aware of their consumption patterns and the height of expenditure on individual categories [18][2][7][13][8]. For this reason, it is speculated that asking a series of simple binary questions increases the simplicity of the artifacts, and therefore makes them more accessible to the citizens.
- **Accessibility** - the artifacts will be available on a public web address and therefore accessible to anyone through a browser without any further requirements such as registration or additional software installations.
- **Comprehensibility** - linked to the simplicity requirement, but focusing on the results interpretation of the Personal inflation calculator, this requirement ensures that the results of the personal inflation estimation can be understood even without extended knowledge on macroeconomics or, more specifically, inflation.
- **Scaling** - this requirement holds relevance for further work, as a research and design principle should be reusable for application on other country data sets.

3.2.2 Target audience

The target audience for the artifacts has been identified as follows:

- **General Public** - besides of the educational function of the Inflation data visualization tool, the Personal inflation calculator has the benefit of providing insights to own consumption patterns, framing them in the context of inflation as price dynamics measure for the scope of analyzing the latter for own consumption pattern. This work speculates that individuals might even alter their consumption habits if their negative effect on the redistribution of own disposable income is proved in the context of price trends. In other words, people might spend less on a certain expenditure category (e.g., transport) if this category is experiencing price inflation, i.e., the price of items in this category (e.g., fuel) is going up.
- **Professionals in the Education branch** - because of the educative nature of both artifacts, especially the Inflation data visualization, the artifacts can be used for educative purposes in schools and other educational facilities and programs.

- **Researchers** - firstly, researchers can benefit from the visual analysis that the Inflation data visualization artifact offers, along with the data download functionality. This allows the researcher to slice or drill down the data to their convenience, and then download the resulting dataset. Secondly, future work in the Personal inflation calculator tool will focus on feedback collected from general public users to provide potential indicators to consumer feedback and consumer confidence.

3.3 Development method

The development of two artifacts differed slightly due to the discrepancies in the familiarity of the requirements beforehand.

The Inflation visualization tool was developed using the incremental and iterative development process with a waterfall model [120] repetitions in the iterative cycles. The process itself is based on a Plan-Do-Check-Act (PDCA) [121] business cycle, and applies to software development where early iterations of software are required for improvement and corrective actions. The reason for deploying this methodology for the development of this artifact was the fact that the requirements were not fully known and specified in advance, so the outcome of each development cycle was presented to the relevant audience for feedback. Based on that input, additional requirements were formulated and incorporated into the development of the next iteration, until the entire project scope was implemented and the final results were delivered [122]. The advantage of this method was that the extent could be altered during development life cycle, a fact that has proven itself beneficial during the production of this artifact.

The Personal inflation calculator, on the other hand, had a clearer set of requirements up front, which required fewer iterations. This, however, implied that the waterfall model was applied to a larger scale on each iteration. An illustrative comparison between the two methods can be observed in Figure 3.2, where time units are represented as an abstraction of time spent on each phase.

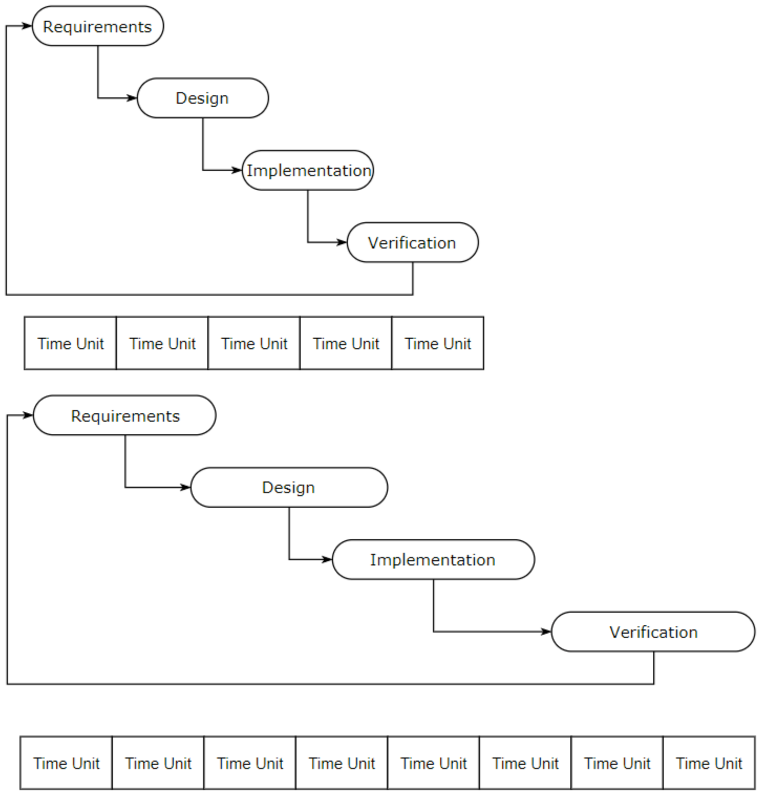


Figure 3.2: Comparison between the methods employed in the development of artifacts - an illustration

3.4 Empirical study

A quantitative method was used for the empirical part of the thesis, in the form of comparing the precision of machine learning algorithms used to build models. More precisely, as shown in Chapter 5, models have been constructed using different machine learning algorithms, to perform exploratory data analysis of the Austrian Consumption Survey. The purpose of this study is to find consumption categories which are decisive regarding clustering consumers into groups with different consumption patterns.

Since the purpose of this exploratory data analysis approach was to generate consumption habits questions, the condition for using the machine learning model was to create decision trees. The reason behind choosing decision trees was their essential property of modeling tree-like graphs with decision points [123], and consequences related to them. This can, therefore, be directly mapped to a series of binary questions asked to the end user, which is the primary scope of the artifact and one of the primary objectives of this work.

The choice of decision tree algorithms came down to 3, implemented in two different tools.

Firstly, Univariate Boosted Decision Tree Regression is a machine learning algorithm that combines classification and regression tree models and fits them together for improving precision [124]. Despite the underlying complexity of incorporating tree-based methods, the apparent advantage is the simplification of the resulting data model into a tree, which satisfies requirements for this data analysis. This algorithm was deployed and used in Azure ML studio [38]. Because Azure ML tool provides only single response variable targeting, the application of this model was in the individual categories. This meant that data was split into 12 clusters, where the response variable at hand was included, along with the demographic data and the explanatory variables directly linked to that category. This resulted in 12 models each regressing over explanatory variables to predict a weight of the individual group.

Secondly, Multiclass Decision Forest in combination with K-Means Clustering was used with the intent of initially clustering the consumption data into some classes, assigning a class label to each data point. After the clustering is performed, the machine learning algorithm was used on the initial data enriched with class labels, to forecast the consumption class. This paradigm was also implemented using Azure ML studio framework, targeting a single response variable of consumption class label.

Thirdly, Multivariate Decision Tree Regression was used to forecast the 12 response variables each corresponding to the weight of 12 consumption categories. This model was built using the Clus tool [37], which, unlike Azure ML, can target more than a single response variable. Multivariate regression, also called multi-target, multi-response or multi-output regression, has proven to be ideal for this task, as it aims to simultaneously predict multiple response variables by constructing a single model [125].

The data preparation part, besides of variable selection and data cleansing, included data binning. The motivation for descriptive data binning can be found in the context of this artifact's deployment and interaction with end users. As Browning and Crossley [126] point out, when designing survey questions, the role of error-ridden measures in finding out the distribution of the quantity of interest cannot be overlooked. In fact, the idea behind binning variables was to trade accuracy for simplicity, as users would not be asked about the correct numerical input of their consumption habits, but rather the estimation of frequency and significance of its expenditure to the disposable income. In other words, building a model founded on binned data allows the application to ask questions such as "Do you eat a lot of meat?" instead of "Is your monthly consumption of meat greater than 100 EUR?". This argumentation also builds upon the theoretical framework set in Chapter 1, where it has been argued that citizens might have a distorted image about their consumption habits, and are therefore inclined not to have accurate information on their spending patterns. With this in mind, the number of bins has consequently been arbitrarily set to 3, with the bin borders set to 25 and 75 percent respectively.

Finally, the models were evaluated. The evaluation was performed with and without data binning, to compare the accuracy change associated with binning data. As Chapter

5 shows, Multivariate Decision Tree Regression has proven itself as most precise machine learning algorithm in the given context and has therefore been used to generate a model, eventually deployed as the underlying questions model in the Personal inflation calculator artifact. Final evaluating step included reporting on using the actual artifact with randomly chosen individuals from the consumption survey to investigate and compare its precision.

3.5 Multi-target Decision Tree algorithms

This section will provide the theoretical background of the Multi-Target Decision Tree algorithm used in the model building process. Before proceeding, however, the title of this section needs to be given a scientific justification.

Firstly, why were decision trees used instead of any other machine learning algorithm? As mentioned earlier in this chapter, the aim of this work is to conceive a model that is used to discover the user's rate of inflation. The usability requirement specified in this chapter states that the users need to input their consumption preferences through a series of consumption habit questions instead of a sequence of their consumption estimations, building on to the hypothesis laid out in Chapter 1. Hence, it was essential to use decision trees, since the decision points forming branches align well with the consumption habits questions requirement. Furthermore, decision tree models are easier to read and interpret, a property which is most valuable when exploring a dataset [127].

Secondly, why was multivariate, also called multi-target, multi-response or multi-output regression decision tree algorithm used, and how come it has proven itself as most precise for the scope of this work? Among the requirements laid out in this chapter is the one on providing an inflation rate estimation on 12 COICOP categories instead of on just the overall inflation rate. This implies that this work deals with estimating multiple target variables instead of a single one. As highlighted by Struyf et al. [127], two alternate approaches can be taken to tackle the problem of class set prediction: building a separate model for each class or using a multi-target algorithm. Besides of work by Dzerovski et al. [128] elaborating on the advantages of using a single multi-target model over multiple single target models, Chapter 5 presents the comparative analysis of the two methods, agreeing with the findings of Dzerovski's work.

Further benefit of multi-target regression models emphasized is the fact that they consider both the relationship between descriptive and target variables, and the relationship between target variables themselves; providing a better representation and interpretation of real-world problems [125][129]

One of the first approaches for dealing with multi-target regression models was proposed by De'ath [130]. This approach was based on univariate recursive partitioning method (CART) [131] applied on a multi-target regression problem. This implies that the multivariate regression trees are built similarly as a CART, meaning that starting with a root node, the instances are split based on a purity criteria until a stopping condition is reached [125]. In fact, this approach differs itself from CART only for its redefinition of the impurity measure as a sum of squared error over the multi-target response

$$\sum_{l=1}^{N}\sum_{i=1}^{d}(y_i^{(l)} - \overline{y}_i)^2 \ ,$$

where $y_i^{(l)}$ represents the value of output variable Y_i for the instance l, $\overline{y}_i$ symbolizes the mean of Y_i for a specific node, N is a number of cluster instances and d number of target variables. To minimize impurity for each of the node splits, each node is selected for which their sum of squares is minimized.

Struyf and Dzeroski [132] improved this basis by proposing a constraint-based system for building multi-objective regression trees (MORTs). Their approach was to provide the user with the possibility of trading precision off for decision tree size and complexity. Moreover, their proposal consists of initially building a large tree and then pruning it based on the extent of size constraints. In this system, MORTs are constructed with the usual top-down induction algorithm [133], with the usage of the intra-cluster variation summed over the clusters (subsets) induced. This procedure can be mathematically described as

$$N\sum_{i=1}^{d}Var(Y_i) \ ,$$

here, $Var(Y_i)$ the variance of target variable Y_i in the cluster. Minimizing the variation between clusters results in bottom instances or leaves that are less impure, ultimately providing better predictions.

Other works include Appice and Dzeroski's [134] multi-target stepwise model tree induction (MTSMOTI), which uses the stepwise model tree induction algorithm [135] to combine several linear models to predict the value of a different target variable Y_i. Kocev et al. [129] compared two methods for resolving the multi-target problem; firstly, they learned models for each variable separately and secondly, a single model for all targets at once.

3.5.1 Predictive clustering

Clus software, co-developed by the Declarative Languages and Artificial intelligence group of the Katholieke Universiteit Leuven, Belgium and the Department of Knowledge Technologies of the Jozef Stefan Institute in Ljubljana, Slovenia [37] is used for building the learning model used in this work. Clus implements the predictive clustering framework [136][137][138], unifying unsupervised clustering and predictive modelling for the scope of multi-label classification and multi-task learning.

Other works using the predictive clustering framework include Ikonomovska et al. [139] incremental multi-variable tree algorithm FIMT-MT. This algorithm extends the incremental single-variable model by enriching it with predictive clustering technology when selecting criteria for splits. Stojanova et al. [140] developed NCLUS, a top-down induction algorithm that recursively partitions nodes based on autocorrelation and average variance reduction on the set of all target variables. Levatic et al. [141] focus on a self-training approach using a random forest of predictive clustering trees to tackle the task of semi-supervised learning for multi-variable regression. The main feature of their algorithm is that in the process of self-learning it iteratively reuses its predictions, the most reliable ones being selected based on a reliability score, based on an average of normalized per-variable standard deviations.

In their definition of predictive clustering model, Blockeel et al. [137] argue that Langley's C4.5 [142] algorithm for supervised clustering can be extended to support unsupervised clustering. They state that this can be done by making use of the distance metric to form clusters, even without providing the class information as done in Langley's supervised method. Applying this reasoning to a regression problem leads to unsupervised regression, for which the relative error can be used as a quality measure. Finally, Blockeel et al. [137] created a top-down induction of clustering trees TIC, by specifying its splitting, stopping and pruning rules.

Splitting

Given a cluster C and a test T, applying T on C will result in two separate clusters C_1 and C_2. TIC computes the distance $d(p(C_1), p(C_2))$ where p is a prototype function. Test T must ensure that the distance between the two clusters is maximized, leading to two distinct clusters, implying that the splitting attribute and its value will be one of the highest information gain [143]. As Blockeel et al. [137] note, this distance-based approach is valid for both numeric and symbolic data, a property which is relevant to this work when taken into account that dataset values are binned, as noted in Chapter 5. As for the prototype function, Struyf et al. [127] suggests taking a Euclidean distance between the vector representation of two valid data sets C_i and C_j:

$$d(C_i, C_j) = d_{Euclidean}(v_i, v_j) = \sqrt{\sum_k \omega_k (v_{i,k} - v_{j,k})^2}\,,$$

where the hierarchical relationship among classes can be adjusted by setting the weights ω_k to appropriate values.

Stopping

Stopping criteria are based on whether splitting the cluster C would hold statistical significance. In the classification context, the χ^2 test is used to check whether class distributions in subtrees have a significant difference [144][145]. Blockeel et al. [137] used an F-test, arguing that regression and clustering use variance as best split condition; meaning that

$$F = \frac{SS_T/(N-1)}{(SS_W)/(N-k)} ,$$

where SS_T represents the total sum of squares, SS_W the sum of squared distances within sets and k is the number of subsets in the partition.

should be large enough to perform the split, or declare the node as a leaf node otherwise.

Pruning

After building the entire tree, pruning is engaged by computing the quality of a tree on a validation set. Methods deployed for this computation are usually predictive accuracy for classification trees and the inverse of the relative error for clustering or regression trees. This strategy has been successfully followed in the context of classification and regression [146] and clustering [147], and is deployed as part of this work, proving itself as an optimal strategy to tackle overfitting [148].

3.6 Dataset

The dataset used for the analysis and final estimation of personal inflation rate is the Austrian Consumption Survey of 2014/2015. Consumption surveys are carried out every five years to gather information on consumption habits of households in Austria and provide data on living standards and conditions of various social groups. The data serve as a basis for studies on the distribution of consumption expenditure within different household groups and is as such a basis for constructing and adequately weighing the consumer price index [149][150]. The survey is composed of 696 variables and 7162 data points, which represent surveyed individuals.

Descriptive variables can be divided into 13 groups. The first group is general demographic data, with categorical variables such as "Terrasse or Loggia available" and continuous variables such as "Apartment surface in square meters". These variables are particularly interesting in the expenditure estimation context for observing the relationship between demographics and expenditure patterns. Other 12 groups are directly linked to the 12 COICOP [151] expenditure categories, and the consumption subcategories which make them up.

The initial dataset selection process included the possibility of using anonymous expenditure data provided by banks. With the onset of tools such as Erste Bank's George online banking [152], consumers can have an overview on their consumption habits as they are linked to their bank accounts and divided into consumption categories, similar to the COICOP classification. Furthermore, the users are motivated to categorize uncategorized expenditures as well as cash withdrawals.

Uncategorized expenditures stem from the inability of online banking systems to categorize specific transaction and link the category of the vendor in question to the type of spending. This, however, can be easily achieved with some manual input from the user. On the other hand, categorizing withdrawals is a tedious task, since, as argued in Chapter 1, people are not aware of their consumption expenditures and their division into different categories. This is then mainly reflected for items which fall into the Frequent Out-Of-Pocket Purchases (FROOPP) [9], transactions most likely to be contained in the "withdrawals" section. In fact, a survey that was conducted as part of this research, yielded average values of 22,95% for uncategorized and 8.85% of withdrawals in a set of 47 individuals.

The dataset required some data normalization, for model building to coincide with the scope of research. Expenditure data needed to be converted to weight data; in other words, each expenditure was divided by the overall spending of that individual to provide the relative weight of that category in the individuals' expenditure spectrum.

CHAPTER 4

Implementation

This chapter will deal with the technical implementation of the underlying infrastructure developed to support the necessary set of functionality for the web interface. Furthermore, the collection of possible interaction with the web interface will be summarized.

With this in mind, the chapter will firstly touch upon the stakeholders and the modules in the sphere of their interest, highlighting the interaction of different modules for analytic purposes. Secondly, the architectural components will be described; and thirdly, the algorithm and mathematical functions used will be elaborated.

4.1 Stakeholders and functionality

The application is primarily designed for researchers, but also for the general population who would be interested in their consumption patterns, and their interaction with broad macroeconomic indicators.

Main stakeholder groups can, therefore, be divided based on the functionality of their interest.

4.1.1 Personal inflation calculator

The core purpose of this function is directed towards estimating personal inflation rate based on statistical data obtained from the Austrian consumption survey from 2014/2015. The data acts as a basis for both the initial construction of the questions asked to the end user, as well as providing an estimation of the personal inflation rate. More details on the statistical methods behind the construction can be found in Chapter 3.

As argued in Chapter 1, the problems addressed by this work is the one that existing Personal inflation calculators require a highly informed input by the user, consisting of the users know exactly what their consumption on specific categories is. This work

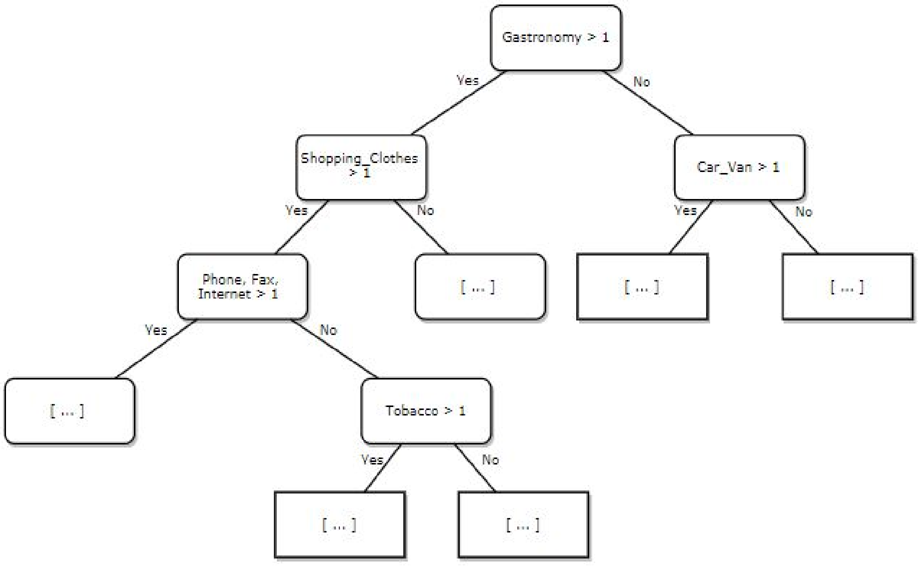


Figure 4.1: Decision Tree model: Concept Illustration

hypothesizes that the way to circumvent this problem is to construct a model which will base on general consumption questions which do not require a high level of knowledge on personal consumption levels. Hence, decision tree algorithm has proven itself as an ideal candidate for constructing a model that fits into this set of requirements. Figure 4.1 illustrates a decision tree concept, similar to the one obtained during the model construction phase of this work.

This binary decision tree model is ideal for following the principles of simplified gesture input for smartphones [153], further reducing the effort needed from the user to produce own inflation rate estimation. Figure 4.2 shows the interface used for the user to input consumption preferences, referencing the root node of the decision tree illustration from Figure 4.1.

Figure 4.3 illustrates the swipe input provided by the user to answer the first consumption question. Swiping the question card to the right produces a "Yes" reply, and navigates down the constructed decision tree to provide the next question, which will, in this case, determine whether the user's consumption pattern fits in the top category of shopping for clothes.

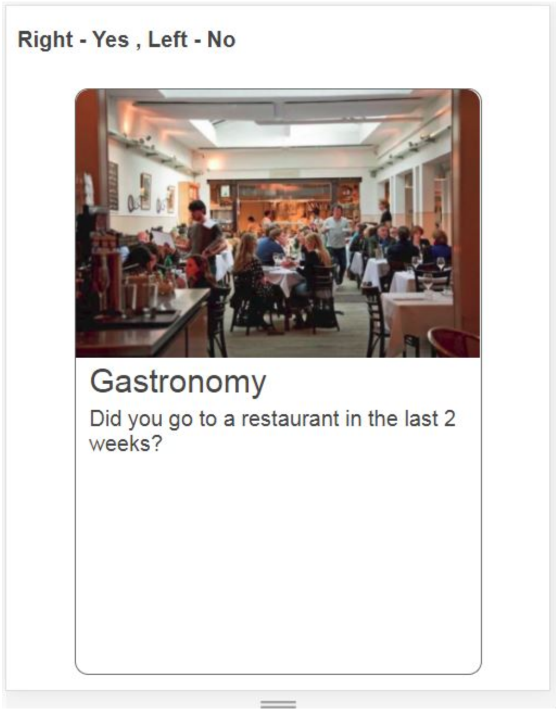


Figure 4.2: Consumption Question - root node

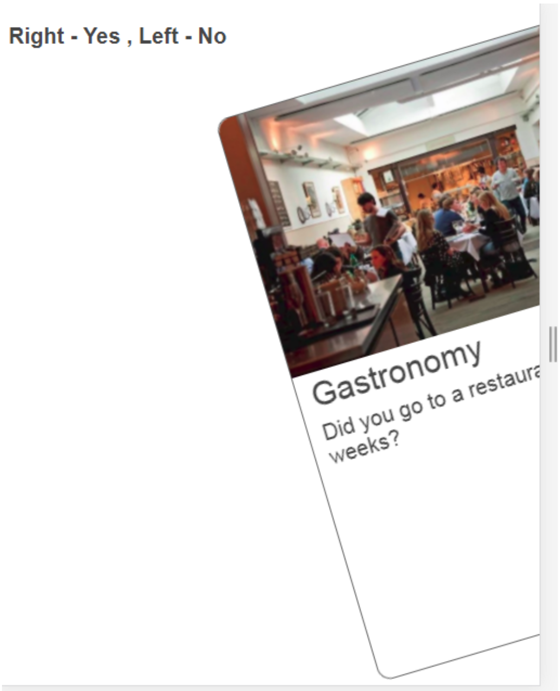


Figure 4.3: Consumption Input - root node

Eventually, after some questions asked as a result of navigating the decision tree, the user will ultimately reach the leaf node, which represents the estimation of their consumption pattern. The latter, represented by percentage weights given to Classification of Individual Consumption According to Purpose (COICOP) [154][151] categories is calculated together with price index changes in order to produce the personal inflation rate for the user, similarly to the calculation of the official inflation rate described in Section 4.5 of this chapter. This rate is shown to the user on the final display screen of the tool, along with the inflation rate for Austria, represented by same 12 COICOP rates, as shown in Figure 4.4, whereas Figure 4.5 represents the official Austrian inflation, divided into 12 COICOP categories.

By comparing Figures 4.4 and 4.5, following conclusions can be made:

- CP07 (Transport) is the most significant inflation driver for this user (1.73 for February 2017 opposed to Austria's 0.93). Hence, in times of high price increases for transport reducing transport expenditure would lower overall price inflation for this user compared to an average Austrian.
- Because this user is highly sensitive to price changes in transport, sinking prices associated with this category lower the overall inflation rate of the user. From the graph it can be observed that the overall inflation rate for Austria is higher (2.33) than for the user (2.20) mostly due to the reduced price index of this category, i.e., sinking prices of transport. This trend can be observed from Figure 4.6, which shows the price trend of CP07 transport category for Austria in the last two years. This figure shows the surge in transport prices in February 2017 which led to an increased inflation rate for individuals that have a significant portion of their disposable income invested in this category.
- Observing the transport price trend for 2016 showcases a substantial deflation occurring for this group during entire 2016. Observing the personalized inflation graph for the user at hand shows that the user was experiencing an overall deflation

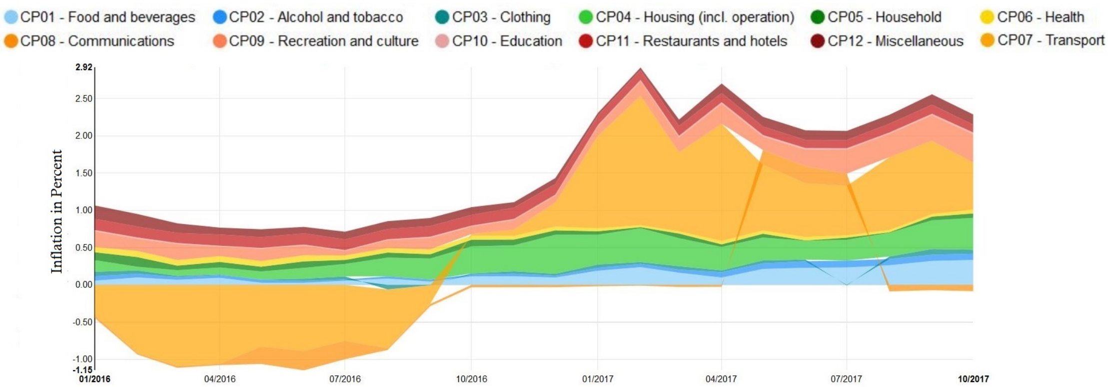


Figure 4.4: Personal Inflation rate by 12 COICOP categories

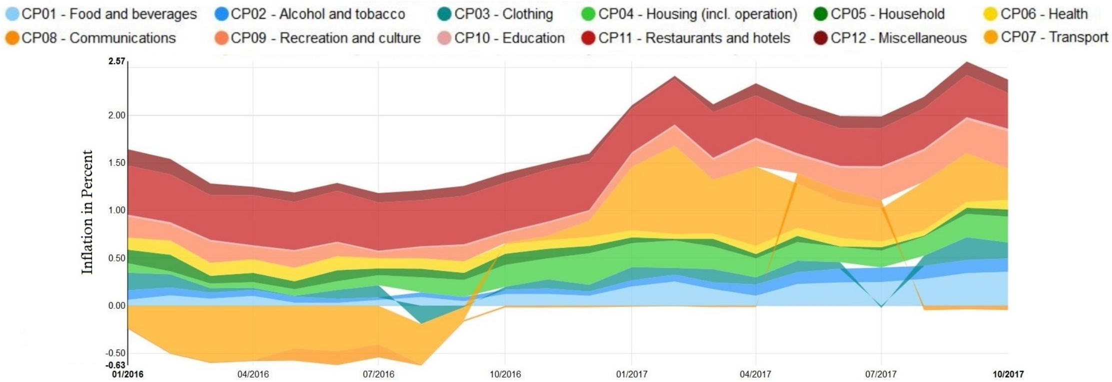


Figure 4.5: Austrian Inflation rate by 12 COICOP categories

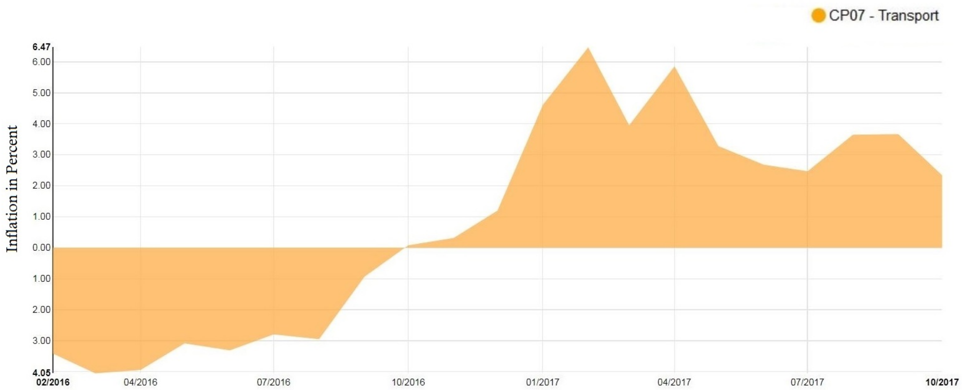


Figure 4.6: Austrian Inflation rate for Transport

from March until September 2016 with a maximum deflation value peaking -0.37 in June 2016. Taking into consideration that Austria was experiencing a slow inflation rate at this point (0.67) leads to the conclusion that the disposable income for this user was "worth" more during this time than the one of an average Austrian. The reason for this discrepancy can be attributed to the primary driver of inflation at this time CP11 - Restaurants and Hotels, which was averaging around 0.5 at the time for Austria, and approximately 0.14 for the user.

This brief analysis serves to illustrate the interaction of different artifacts of this work for the scope of analyzing macroeconomic forces and components influencing the overall outcome of inflation as a key economic indicator.

4.1.2 Historical data visualization

Module aimed at for both researchers and the general public is the historical data visualization which can be leveraged for purposes of macroeconomic analysis of inflation

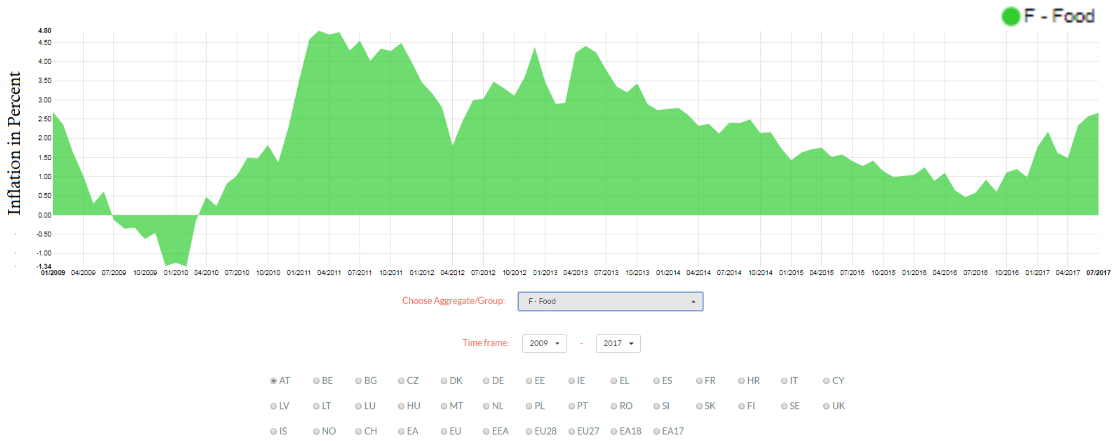


Figure 4.7: Food inflation in Austria

in a given period. Each view also provides the possibility of downloading data being visualized in most common data formats for further transformation and calculation. That implies that the scope of this particular use case extends to not only the visual investigation but also provides means for additional analysis which can be performed by downloading data at hand. This section will give some basic examples of how macroeconomic analysis can be accomplished by drawing conclusions from the displayed graphs.

Data is obtained directly from Eurostat web service [155] on a monthly basis for EU and EEA countries, and is comprised of 6 views:

Inflation rates by country and class

This view enables the user to visualize individual inflation categories per country. Figure 4.7 provides an example of such visualization where inflation figures for category "Food" are displayed for the period between 2009 and 2017. The controls are also visible, which allow the user to set the time span, category, and country of interest.

The scope of this view is to provide essential data on the inflation trend of a specific country and category.

From Figure 4.7, one can observe that the price trends for food have been going upward since 2010.

Cross-country comparison

This view enables the user to compare individual inflation categories between an arbitrary number of countries. Figure 4.8 provides an example of such visualization where inflation figures for category "E1 - Electricity, gas, heat inflation comparison" are displayed for the period between 2011 and 2016.

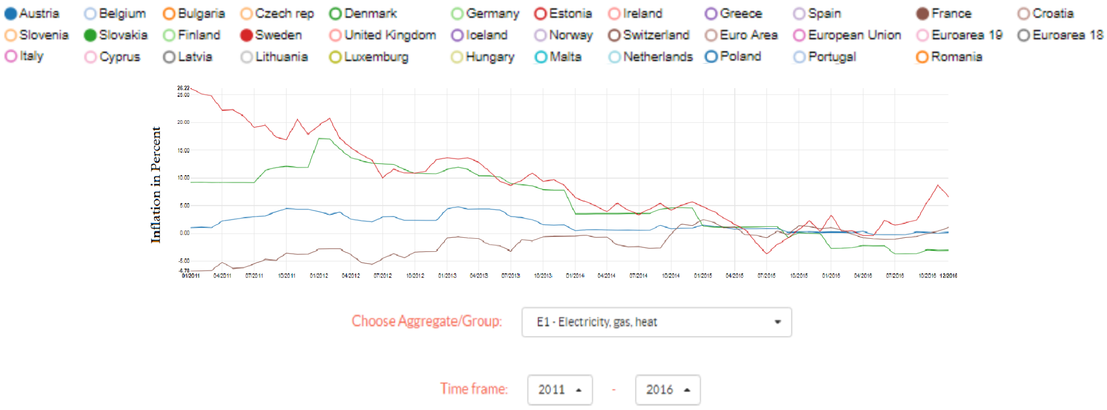


Figure 4.8: Inflation rate (in percentage points) of E1 - Electricity, gas, heat inflation comparison in Austria, Slovakia, Sweden and France

The scope of this view is to provide means for researchers to compare different inflation categories among different EU and EEA countries naturally and intuitively.

What can be observed in Figure 4.8 is that, for instance, Sweden had a relatively high inflation for this category in 2011, whereas France had a period of deflation for this category in the same time. It can also be noted that eventually, all values converged to a relatively low inflation rate by the end of 2014.

Contribution to inflation by 4 special aggregates

Using Eurostat's nomenclature specified in its Reference And Management Of Nomenclatures (RAMON) classification [156], the inflation rate in this view is split into four main contributing categories for a specified country. These four categories are taken from RAMON's list of special aggregates:

1. **NRG - Energy** - Includes electricity, gas, liquid fuels, solid fuels, heat energy, as well as fuels and lubricants for personal transport equipment.
2. **FOOD - Food including alcohol and tobacco** - goods such as bread, meat, fish, milk, fruit, vegetables, coffee, spirits, beer, wine, tobacco etc. are included here.
3. **IGD_NNRG Non - energy industrial goods** - include clothing material, garments, water supply, materials for dwelling maintainance, carpets and household textiles, glassware, non-durable household goods, pharmaceutical products, motor cars, cycles and bicycles, books, newspapers, jewellery, toys etc.
4. **SERV - Services** - overall index excluding goods; including services such as cleaning, rentals, various dwelling and surroundings maintenance services, such as

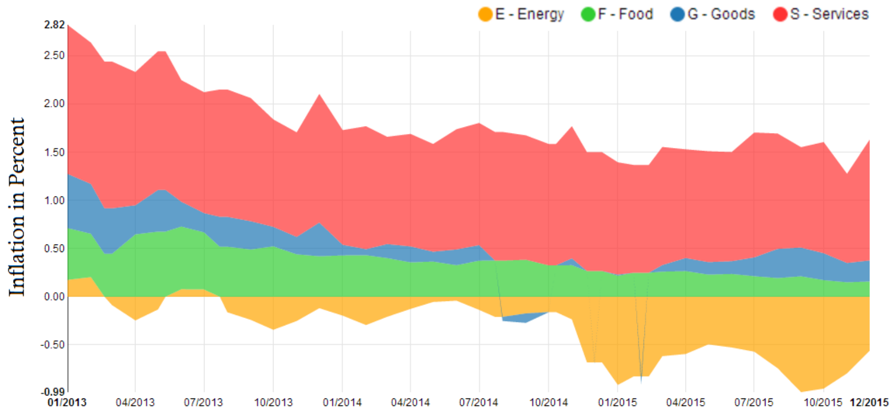


Figure 4.9: Contribution of Main Aggregates to Inflation in Austria (in percentage points)

repair of household appliances, domestic services, swereage collection. Personal or cargo transport by any means is also included, as well as holidays, hairdressing salons, insurance, restaurants etc.

As an example, the inflation rate of Austria in the period between 2013 and end of 2015 can be observed in Figure 4.9.

These special aggregates encompass the entire consumption within an economy, and their sum makes up for the inflation figure. Each of these categories has a contributing weight associated with it, which depends on the consumption pattern of an average user. The weights are officially adjusted on a yearly basis, based on the consumption pattern, which is defined using analyzing consumer baskets.

A conclusion that can be drawn by observing Figure 4.9 is that services category has been the most significant driver of inflation in Austria in the period from 2013 to the end of 2015. It can also be observed that in the same time, especially from the end of 2014, energy was slowing the inflation rate down, almost compensating for the factor services have brought in to increase inflation in Austrian economy [157][92].

Contribution to inflation by 12 sub-aggregates

In this view, the inflation rate is split into 12 sub-aggregate categories for a specified country. Similarly to the previous section, when inflation was divided into four main groups, 12 sub-aggregates provide another method for analyzing factors contributing to the overall inflation rate. Moreover, the 12 special sub-aggregates represent a lower hierarchical level of inflation rate analysis, and are therefore associated with the four special sub-aggregates, in a manner described in the list below:

1. **ELC_GAS - Electricity, gas, heat** - related to the NRG special aggregate, this sub-aggregate encompasses electricity, gas, solid fuels and heat energy part of NRG.
2. **FUEL - Liquid fuels** - represents part of NRG containing liquid fuels and fuels and lubricants for personal transport equipment.
3. **FOOD_P - Processed food** - is associated with special aggregate FOOD, and entails processed food; such as bread cereals, mils, coffee, sugar etc, as well as alcohol and tobacco.
4. **FOOD_NP - Unprocessed food** - all parts of FOOD which are not included in processed food; meat, fish, fruit and vegetables.
5. **IGD_NNRG_D - Durable goods** - Non-energy industrial durables, associated with IGD_NNRG category such as motor cars, furniture, photographic equipment, computers, clocks, motorcycles and bicycles and so on.
6. **IGD_NNRG_SD - Semi-durable goods** - covers goods under the IGD_NNRG category such as clothing, household textiles, glassware, tools and equipment, sports equipment, books, etc.
7. **IGD_NNRG_ND - Non-durable goods** - non durable IGD_NNRG goods, such as water supply, pharmaceutical products, plants, newspapers, dwelling repair and maintenance materials, electric appliances, etc.
8. **SERV_COM - Services: Communication** - communication related services associated with SERV category; such as postal or telephone/telefax related services.
9. **SERV_HOUS - Services: Housing** - housing related services such as refuse and sewerage collection, rentals paid by tenants, maintenance and dwelling repair services, insurance connected to dwelling, etc.
10. **SERV_TRA - Services: Transport** - part of SERV which entails all transport related services, as well as the equipment maintenance and repair as well as insurance connected with transport.
11. **SERV_REC - Services: Recreation** - services related to recreation, including repairs and personal care.
12. **SERV_MSC Services: Miscellaneous** - covers uncategorized services, such as dental, hospital, social and insurance connected with health.

Similarly to the analysis of four special aggregates, Figure 4.10 also shows the inflation rate of Austria in the period between 2013 and end of 2015 for 12 special sub-aggregates.

As with four special aggregates, each of these categories has a contributing weight associated with it, which depends on the consumption pattern of an average user. The

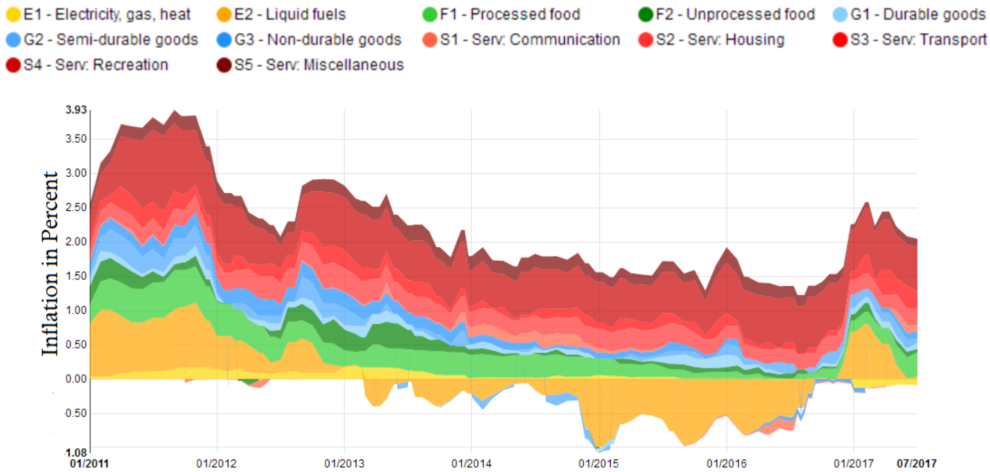


Figure 4.10: Contribution of Sub-Aggregates to Inflation in Austria (in percentage points)

weights are officially adjusted on a yearly basis, based on the consumption pattern, which is defined using analyzing consumer baskets [3].

It is easily observable that Figure 4.10 and Figure 4.9 are in fact similar. This is explained by the fact that the 12 sub-aggregates simply divide the 4 special aggregates into lower-level categories, a feature which is visually represented on the graph by depicting the 12 sub-aggregates in different shades of the same color the higher level category is represented in Figure 4.9. So, for example, Energy in Figure 4.9, visually represented by yellow, is reflected in Figure 4.10 by E1 and E2, each visualized in their own shade of yellow.

Contribution to inflation by 12 COICOP groups

In this view, the inflation rate is split into 12 COICOP groups for a specified country. Similarly to the previous sections, 12 COICOP groups provide another method for analyzing factors contributing to the overall inflation rate. For the sake of providing an easier explanation, Figure 4.11 also shows the inflation rate of Austria in the period between 2013 and end of 2015. The chart is divided into 12 contributing categories [151]:

1. **CP01 - Food and beverages** - the products included in this category are all food products which are intended to be consumed at home. That means that all food products sold for immediate consumption not at home are not included in this category, but rather in the CP11 Restaurants and hotels.

2. **CP02 - Alcohol and tobacco** - this category includes alcoholic beverages that are to be consumed at home; namely low- or non- alcoholic beverages generally alcoholic. Alcoholic drinks consumed outside of household are likewise included in CP11. Tobacco and narcotics, such as marijuana, cocaine, opium and their

derivatives, however are fully included in this category, regardless of the whereabouts of its consumption.

3. **CP03 - Clothing** - clothing material, garments, footwear as well as expenses related to clothing or footwear maintenance are included in this category.
4. **CP04 - housing (incl. operation)** - Rentals, dwelling repairs, water, gas and electricity supply for the household are included in this category.
5. **CP05 - Household** - furniture, furnishing, household textiles, appliances and their maintenance, including tools for household maintenance are parts of this category.
6. **CP06 - Health** - this category entails medical products and appliances as well as outpatient and hospital services.
7. **CP07 - Transport** - purchase and operation of vehicles, as well as expenses related to their maintenance are captured in this category. Furthermore transportation services, such as road, railway or air transport are included as well.
8. **CP08 - Communications** - postal and telephone services and equipment make up this category.
9. **CP09 - Recreation and culture** - audio video equipment, Durables for recreation and culture, pets, gardens as well as recreational and cultural services, newspapers and magazines.
10. **CP10 - Education** - all levels of education, as well as forms of education not definable by level.
11. **CP11 - restaurants and hotels** - Catering and accommodation services.
12. **CP12 - Miscellaneous** - personal care, insurance, social protection, financial and other services [151].

As with previous categorizations, each of these categories has a contributing weight associated with it, which depends on the consumption pattern of an average user. The weights are officially adjusted on a yearly basis, based on the consumption pattern, which is defined using analyzing consumer baskets [3].

As opposed to the similarity identified between Figures 4.10 and 4.9, Figure 4.11 seems to be following a different assignment between groups. This is because the COICOP approach views the differences from a consumers' perspective, rather than Sub-aggregates which are oriented more towards the producers' perspective [156].

The division of basic inflation rate, CP00 into different aggregates is summarized in Figure 4.12.

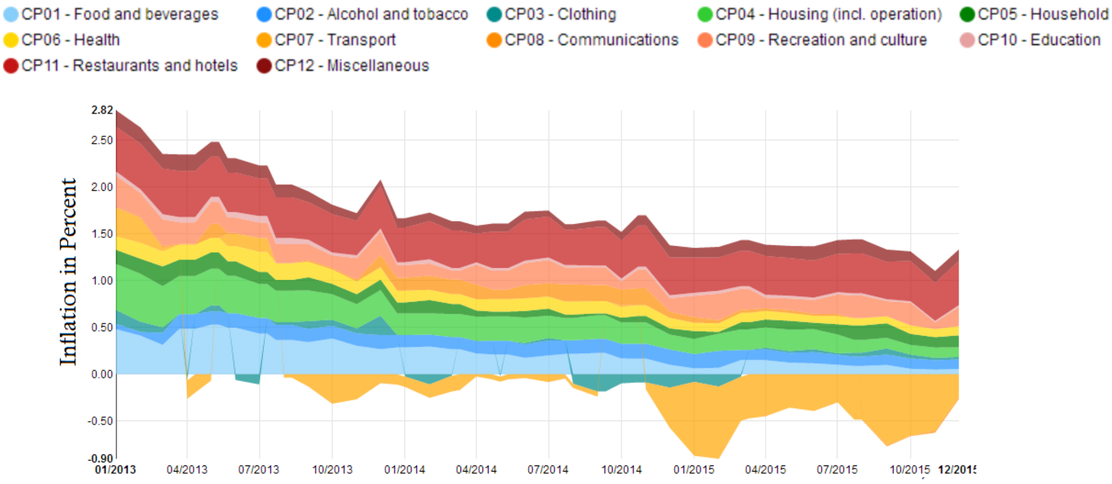


Figure 4.11: Contribution of COICOP categories to Inflation in Austria (in percentage points)

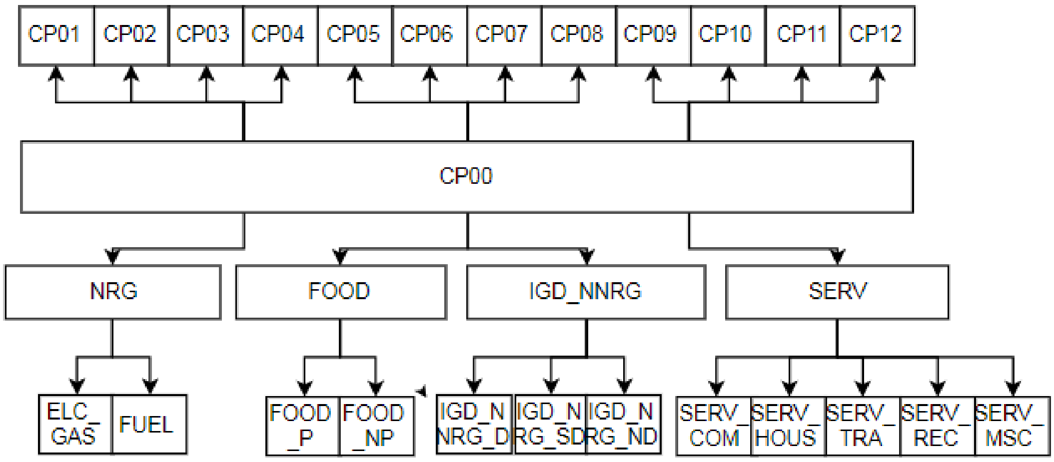


Figure 4.12: Division of CP00 into different aggregates

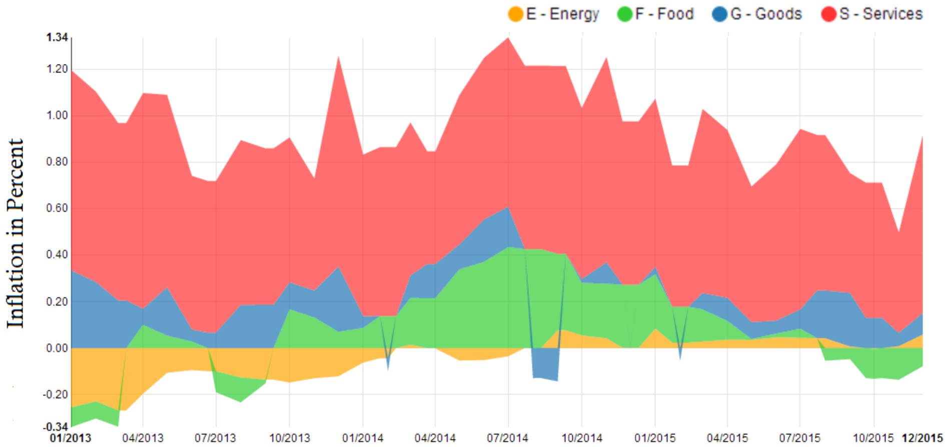


Figure 4.13: Structure of the Inflation differential between Austria and Eurozone (in percentage points)

Inflation differential between two countries

In this view, the Contribution to inflation by four special aggregates graph is visualized, with the underlying data being the differentiation in categories between two countries being compared. The resulting chart indicates two main points: the difference between the inflation rates of comparing nations as well as the source of the difference.

The algorithm used to determine the values for this graph is as follows: Given that country A is being compared to country B, on 4 categories X,Y,Z and W - for each category the difference between the respective value for A and B is taken as the value for the category in the resulting contribution graph. Note that the category values are composed of the indicator and weight calculation, as described in Mathematical Methods section.

$$X(Diff) = X(A) - X(B)$$
$$Y(Diff) = Y(A) - Y(B)$$
$$Z(Diff) = Z(A) - Z(B)$$
$$W(Diff) = W(A) - W(B)$$
$$Sum(Diff) = X(Diff) + Y(Diff) + Z(Diff) + W(Diff)$$

The values for each of the differentiation categories make up the total sum on the contribution graph, as in Figure 4.13

The best way to illustrate the functionality of this graph is by an example. If the month of April in 2014 is taken as an example, the values from Figure 4.13 read the following values:

1. Total: 0.85
2. Services: 0.48
3. Goods: 0.15
4. Food: 0.21
5. Energy: 0.00

From these values, following conclusions can be drawn:

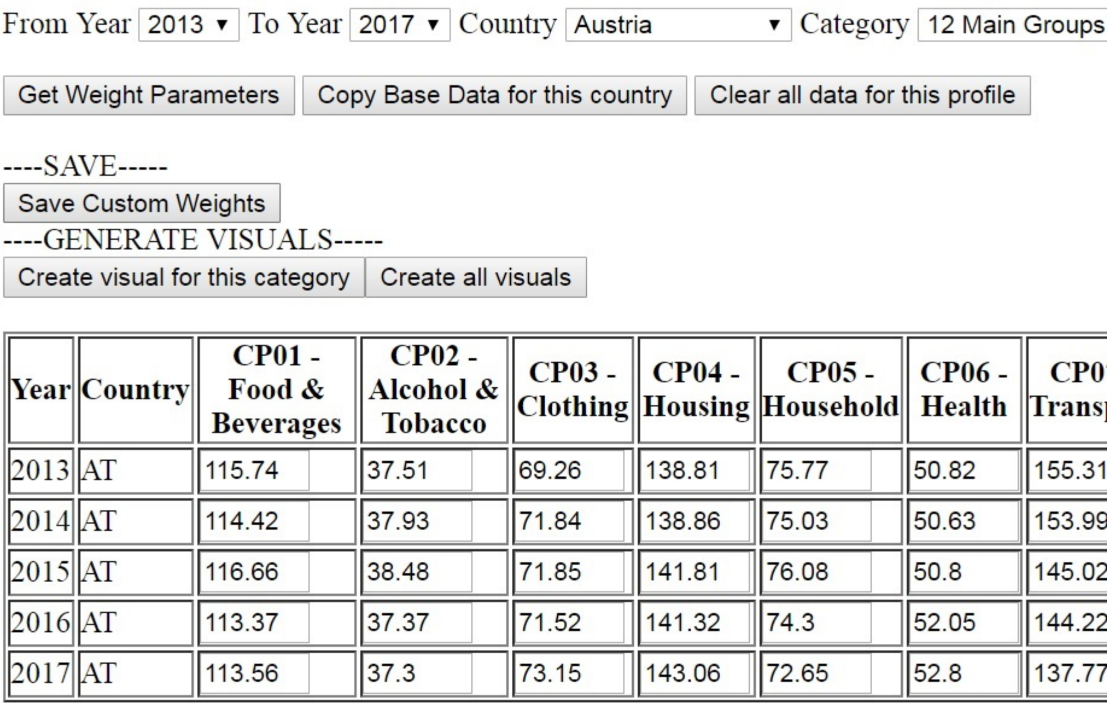
- Inflation in Austria is higher than Eurozone by 0,85 percentage points.
- For Services, Goods and Food inflation level in Austria is higher than Eurozone's.
- The biggest driver behind the difference is the Services sector.
- Austria and Eurozone have the same level of inflation on Energy.

4.1.3 Manual weights and indices editing interface

This functionality is aimed mainly towards researchers whose aim is to explore the effects of different consumption weights on the current inflation rate. Furthermore, the interface provides the possibility to input forecasted indices, to observe the impact of custom weights on future inflation rates. Figure 4.14 shows a weight editor prototype developed as part of this work.

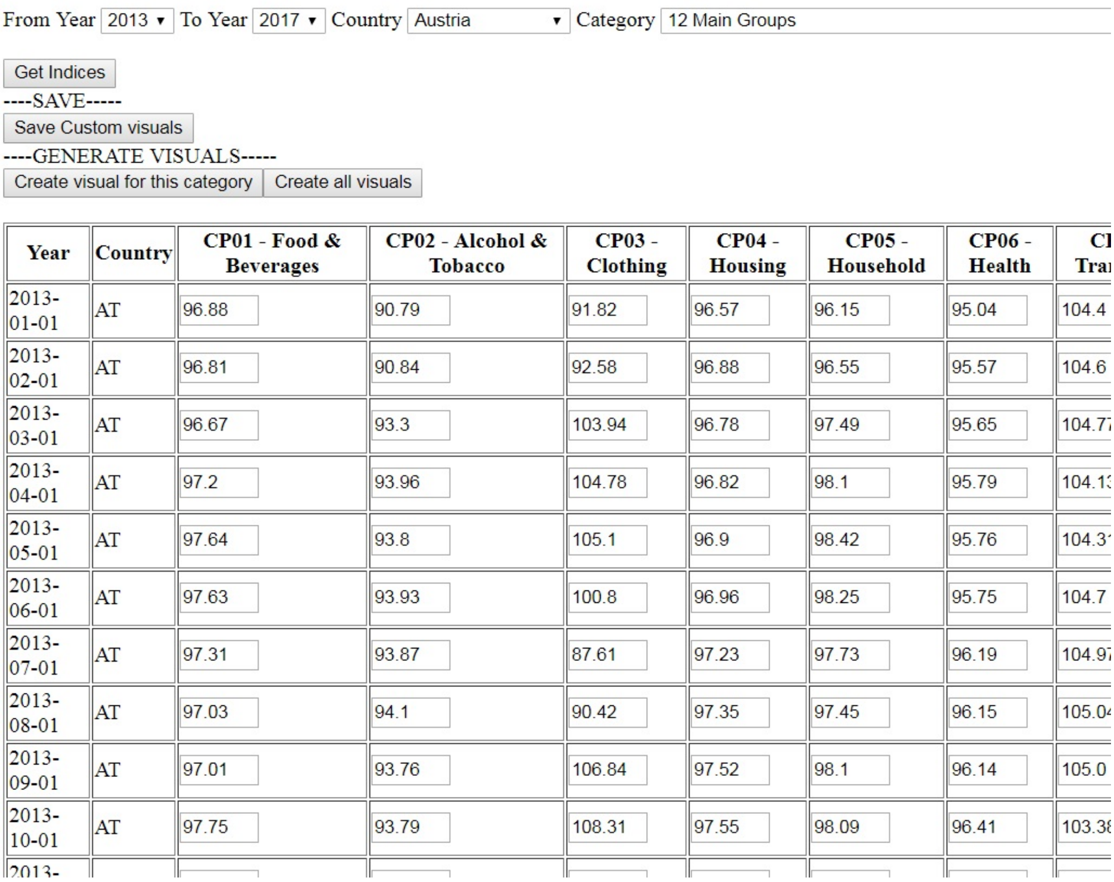
Furthermore, one can also edit forecasted indices, as displayed in Figure 4.15. The main idea is to input indices missing (November and December, denoted with 0) at the time of writing this thesis, to provide a forecast on price trends for selected categories.

Editing the weights in the weight editor and providing a mock price indicator forecast for 12 COICOP categories for November and December 2017 results in an inflation diagram for Austria as shown in Figure 4.16. In this mock scenario, transport price has experienced a significant increase, as a result of an oil price shock, for example. The resulting simulated transport price chart can be observed in Figure 4.17.



Year	Country	CP01 - Food & Beverages	CP02 - Alcohol & Tobacco	CP03 - Clothing	CP04 - Housing	CP05 - Household	CP06 - Health	CP0 Trans
2013	AT	115.74	37.51	69.26	138.81	75.77	50.82	155.31
2014	AT	114.42	37.93	71.84	138.86	75.03	50.63	153.99
2015	AT	116.66	38.48	71.85	141.81	76.08	50.8	145.02
2016	AT	113.37	37.37	71.52	141.32	74.3	52.05	144.22
2017	AT	113.56	37.3	73.15	143.06	72.65	52.8	137.77

Figure 4.14: Consumption weights editor for 12 COICOP categories - an excerpt


From Year 2013 To Year 2017 Country Austria Category 12 Main Groups

Get Indices
----SAVE-----
Save Custom visuals
----GENERATE VISUALS-----
Create visual for this category | Create all visuals

Year	Country	CP01 - Food & Beverages	CP02 - Alcohol & Tobacco	CP03 - Clothing	CP04 - Housing	CP05 - Household	CP06 - Health	Cl Tra
2013-01-01	AT	96.88	90.79	91.82	96.57	96.15	95.04	104.4
2013-02-01	AT	96.81	90.84	92.58	96.88	96.55	95.57	104.6
2013-03-01	AT	96.67	93.3	103.94	96.78	97.49	95.65	104.7
2013-04-01	AT	97.2	93.96	104.78	96.82	98.1	95.79	104.1
2013-05-01	AT	97.64	93.8	105.1	96.9	98.42	95.76	104.3
2013-06-01	AT	97.63	93.93	100.8	96.96	98.25	95.75	104.7
2013-07-01	AT	97.31	93.87	87.61	97.23	97.73	96.19	104.9
2013-08-01	AT	97.03	94.1	90.42	97.35	97.45	96.15	105.0
2013-09-01	AT	97.01	93.76	106.84	97.52	98.1	96.14	105.0
2013-10-01	AT	97.75	93.79	108.31	97.55	98.09	96.41	103.3
2013-								

Figure 4.15: Indices editor for 12 COICOP categories - an excerpt

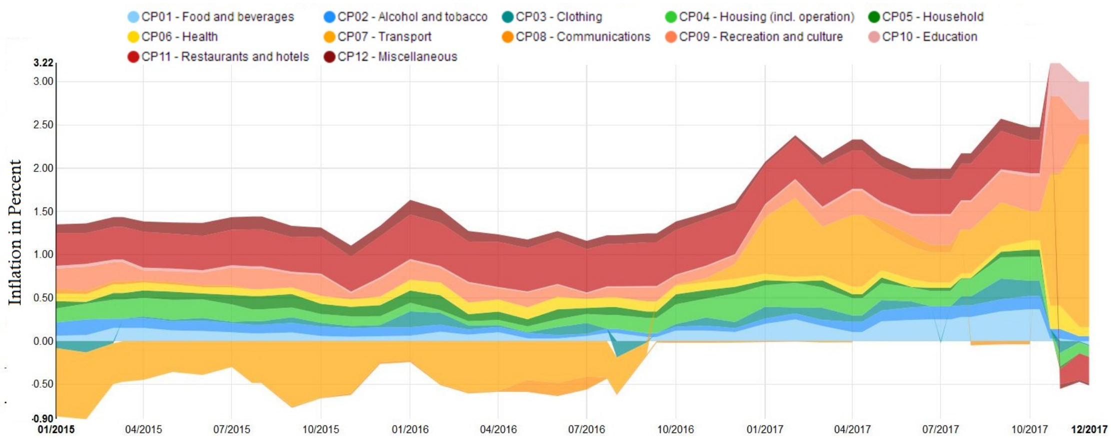


Figure 4.16: Inflation Forecast for 12 COICOP categories

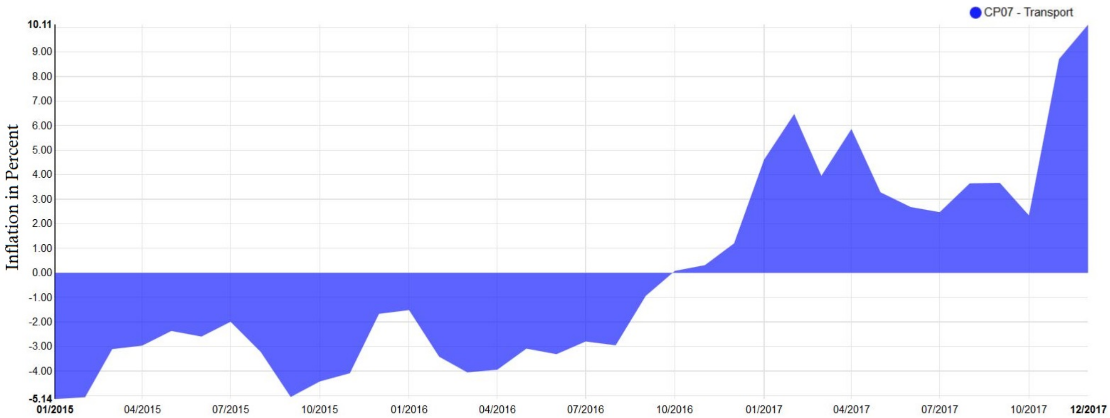


Figure 4.17: Transport price inflation: a simulated scenario

4.2 Technological architecture

This section will focus on the technology which was used for the scope of implementing the system to support the set of the functionality described. Firstly, architectural details will be elaborated, most notably the deployment architecture, providing a high-level overview of the infrastructure and the modules developed and deployed. Deployment architecture will be visualized in Figure 4.18, after which individual components will be dissected and discussed, providing the reasoning behind the choice. This section will, therefore, elaborate the choice of Python as a programming language to develop control modules, as well as MySQL database as a data storage system, and finally, the usage of JQuery with D3.js library for data visualization. This section will also explain how the Model-View-Controller (MVC) pattern was used, and will, therefore, set the stage for next parts which will go in more detail into the implementation of the model in this system.

4.2.1 Deployment Architecture

Figure 4.18 displays a deployment architecture of the system, providing a high level overview on the components used and the processing modules.

The entire system is running on a single Ubuntu server and is comprised of two main components; the user interface and the back end.

The back end has an orchestration layer, a series of shell scripts, which coordinates the execution of modules with the set of passed commands and arguments. The modules whose performance the orchestration layer coordinates are written in python, and they are grouped around three functions:

- **Data Fetcher** - whose role is to fetch data from either Eurostat webservice and/or other sources
- **Data Loader** - the role of this module is to extract relevant saved data from the database and prepare the data for visualization
- **Custom data writer** - the role of this module is to write custom weight and/or indicator data for the selected profile

For reasons of limited resources and the conceptual nature of the system, it is deployed on a single server; although the application would scale well by assigning a dedicated MySQL server, decoupling the processing logic from the storage regarding resource management. Python was the programming language of choice primarily because of the need for a robust and efficient scripting language for scientific computing, syntactic simplicity, and modular architecture [158]. Due to the fact that Python ranks at 7 in the TIOBE Programming Community Index [159], it is a widespread language of choice among large organizations such as Google, CERN or NASA [158], hence it has already

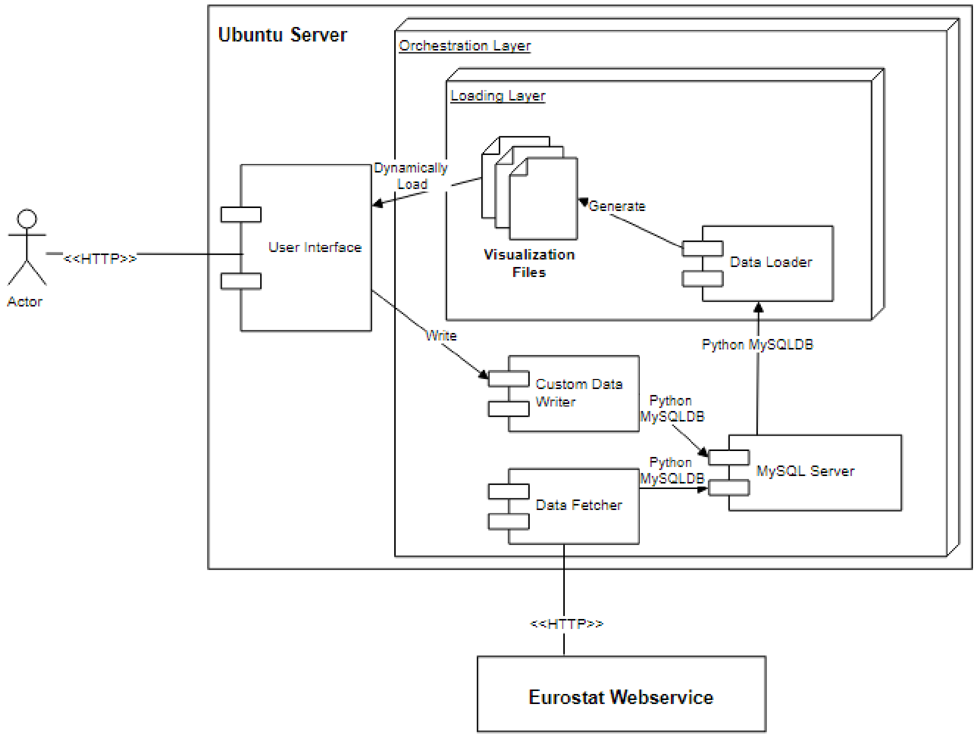


Figure 4.18: Deployment diagram

established itself as a dominant scripting language, and obtaining knowledge of it was another desired side effect during the development of this system. Python is released under Python software foundation license, which is a permissive free software license compatible with the GNU general public license [160].

A MySQL database has been used as a data persistence system due to its popularity among Open Source SQL database management systems, as well as its compatibility and performance with Python programming language [161][162], chosen as the backbone language of the system's back end. Due to the requirement of fast data loading and processing, MySQL database server is seen as an ideal choice for the task. It provides scaling possibilities, as it can handle terabyte-sized databases [163]; in case the project would include more massive data sets with global indicators, as well as importing other crucial macroeconomic performance indicators for visualization and analysis.

D3.js is a specialized JavaScript library for producing interactive visual representations of data. [164][165] It serves as the primary engine behind visualizing all data in the presentation layer of the system. Since it relies on data files in JSON format, the primary goal of the data loader is to produce JSON formatted files to be used for front-end visualization by the D3.js library.

Another reason behind choosing D3.js is also its portability, as it is embedded within

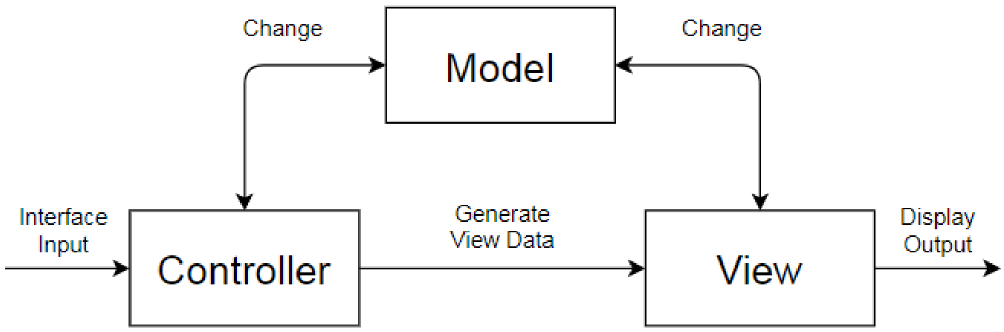


Figure 4.19: Model View Controller(MVC) Pattern, adapted from [169]

HTML website, and it leverages standard JavaScript functions, reducing the necessity of importing third-party libraries. The stacked area graph [166] has proven itself ideal for visualizing the contribution dynamics of inflation data, that is, for visually displaying the categories contributing to the formation of the overall inflation rate.

D3.js is licensed under a Berkeley Software Distribution (BSD license) [167], which allows redistribution and use in source and binary forms with or without notification.

4.2.2 Model-View-Controller Pattern

During the implementation, software patterns [168] were taken into account to better plan and organize development, for purposes of providing reusable, decoupled code promptly. Furthermore, designing a system in this manner offers the possibility to scale the architecture in case a higher volume is required.

In this regard, implementation of the system was based on a Model-View-Controller pattern. As Bucanek [169] states, MVC pattern is one of the most relevant models in computer science but also warns that it is more a philosophy than a recipe. This design describes the architecture as a system of objects, where each object acts in a specific role and performs actions associated with it. The nature of this pattern relies on three primary objects on which the system is split

- **Model** - Model is, in its essence, the object which represents the knowledge and state of the system. It is used to store the data leveraged and used by view and controller, as well as the system state. To encapsulate the object following MVC pattern, Model should not contain any processing logic which pertains to other objects of the system, but should only include logic which aims to fulfill the fundamental mission of the object; representing knowledge and state. Applying this philosophy, the Model object is responsible for importing, processing and storing data related to all functionality of the system. This means that all inflation data, including general statistical data, as well as personalized inflation contributing weights, will be imported, processed and stored. Furthermore, the questions necessary to analyze the user's personal consumption habits are stored and leveraged in other layers for the internal workings of their processing logic. A model object usually provides a communication interface to View and Control, that is, the other objects do not access it directly to manipulate or store data, to achieve encapsulation of functionality. Technology associated with this system to the Model object is the database along with the fetching and customs import logic.

- **View** - View object not only visualizes the Model but should also provide capabilities of highlighting the selected properties of it. Moreover, it also includes interaction possibilities to the end user, which are passed forward to the Controller, and eventually back to the Model object in the form of a feedback. In this system, the View object is realized through HTML and JQuery with D3.js library, providing the end user not only with visualization of data stored in the Model object, but also controls which allow the user to trigger actions in Controller object which will eventually generate new knowledge artifacts in the Model. As an example, the user can create custom weighs in the interface (View), triggering custom weight calculation and generation (Controller), that will eventually generate a new database object (Model). Moreover, the way back can again be followed: the new database object or profile can then be used to generate new visualization graphs (Controller) which are then presented to the user (View) and can be adjusted if needed.

- **Controller** - This object acts as a connector between the Model and its View, so its primary function is to interpret the model for its usage and presentation to the end user. In this system, the Controller is implemented as a series of loading modules written in Python, that have a primary purpose of using mathematical models to transform a set of category indicator values and contribution weights to data written in JSON format that can be read by the View object. As an example, the contribution graph Controller module would interact with the Model, grabbing indicator and contributing weight values, leveraging the values to calculate the contribution parameter for each point in time. These points are then written into files which act as a data source for contribution data visualization module in the View object. In the View object, the user is displayed with controls which enable it to select between visualizing different inflation contribution graphs based on country and period. Switching between countries would mean that the View object would switch between various files generated by the Controller object, which thus fulfills its primary function as a connector between the user interface and knowledge representation in the system.

Figure 4.20 reuses the deployment diagram to illustrate how the Model-View-Controller pattern was used. To summarize, Model object entails knowledge fetching, processing, and storage, Controller loads the data, apply mathematical models on it and loads the files which are prepared for the View object, which either fetches generated files from the Controller or interacts with the Model; based on actions performed by the interface user.

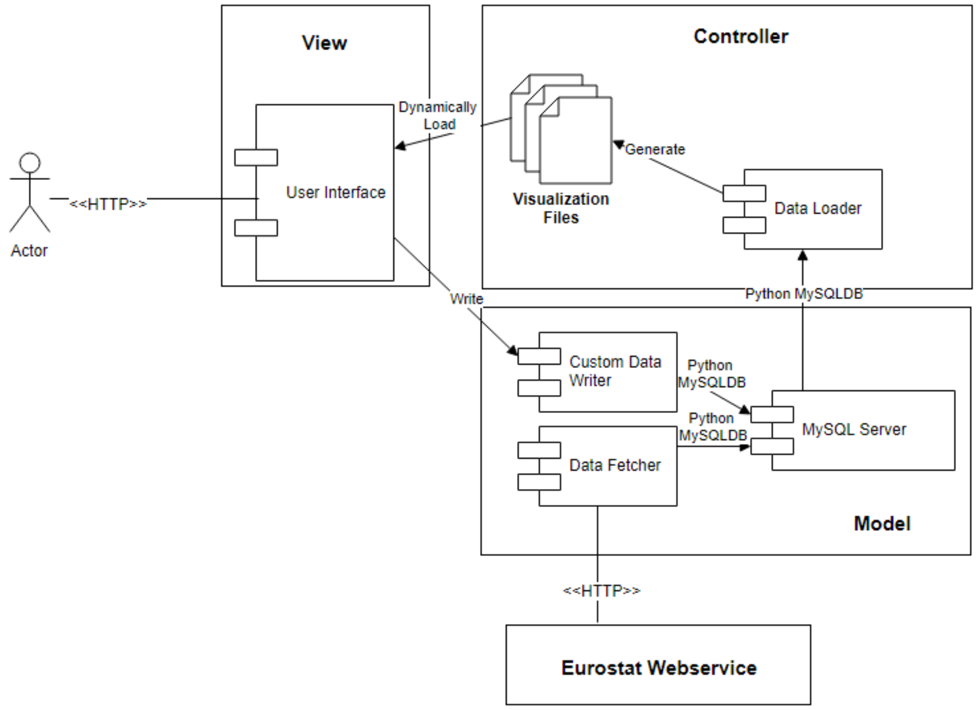


Figure 4.20: Model View Controller(MVC) Pattern, as applied on the system

4.3 Data model

This section describes the underlying ER model supporting the application by providing knowledge and model repository. The implementation of application access to the repository will be described as well.

4.3.1 Database scheme

Database schema was used for describing the relationship between different knowledge representation entities of the application. The scheme was initially developed based on concept requirements and was expanded along the development process as the need arose for further functionality and knowledge storing.

Before providing the visualization of dependence relationship between knowledge artifacts, they will be described shortly:

- **Countries** contains metadata for the countries that will be displayed in the overall representation. Different countries are used in the general overview to identify global macroeconomic trends, but also serve as a basis for personalizing inflation data for a selected country.

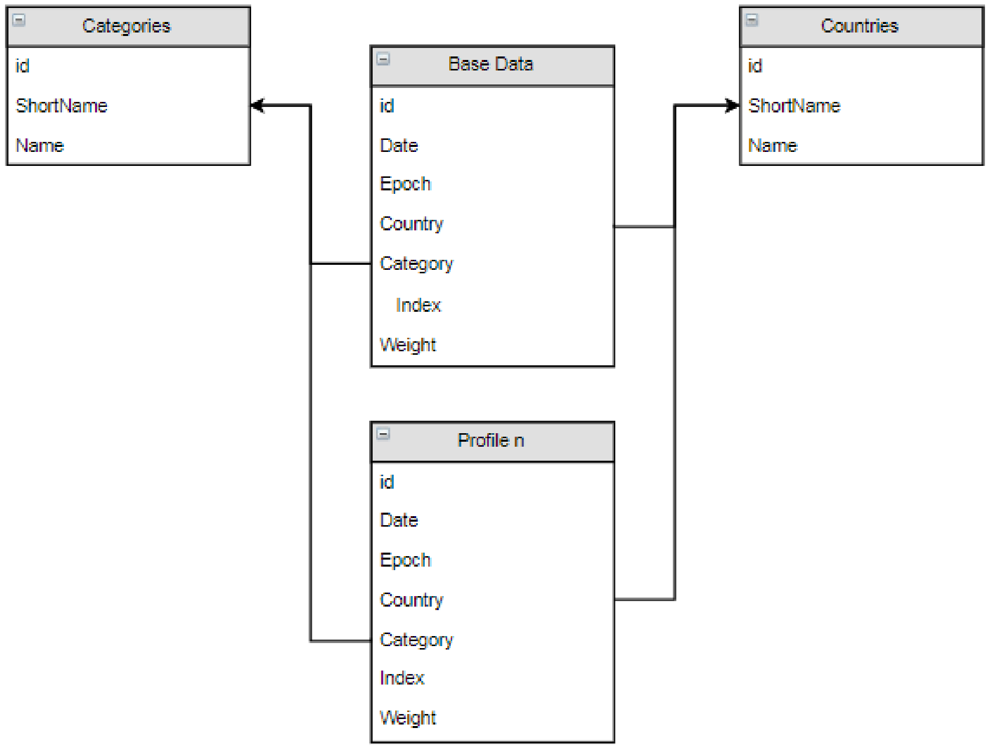


Figure 4.21: Database scheme

- **Categories** contains metadata on categories which are used for inflation data analysis, with different groups representing different levels of aggregation as explained earlier in this chapter.

- **Base Data** this table represents time series data for groups and countries. This entity is, in fact, the basis for inflation data visualization and modification, as inflation data is time series based. Moreover, the table is replicated for individual profiles, since it will be used to initially retrieve and then eventually modify data of interest, to generate custom inflation data for the custom weight and indices interface. Each profile associated with personalizing inflation data has a dedicated time series table, as they can differ based on the parameter specified by the end user.

MySQL was used for database implementation, along with its controllers mysqli for PHP and MySQLdb for Python modules. MySQL was chosen because of its advantages such as:

- Software including all its necessary modules is a well-established solution with a vast community support.

- It is a good fit for the data set in question, and it furthermore leverages on Structured Query Language (SQL) for data insertion and retrieval.
- Highly compatible and simple to configure on Ubuntu Linux system, running on a cloud web instance, which is the basic technology layer used for the development of this project [170].

4.3.2 Data fetching and import

The knowledge base on which the application is based is obtained from Eurostat's SDMX web service. Eurostat contains a vast data set of various economic indicators, and the one relevant for this use case is the HICP inflation data; updated on a monthly basis [155].

Data is fetched on a monthly basis from Eurostat and inserted into the local database. The local database, hence, represents a copy of the Eurostat database. The data loaded from Eurostat represents a baseline with which personalized inflation data can be compared to understand the difference between personal inflation based on individual consumption, and general inflation rate based on a consumer basket of an average citizen.

Besides of the Eurostat importer, which leverages Eurostat's SDMX web service, fetching information in XML format, there is a custom JSON importer in place which is used to import custom JSON data into the database.

The primary motivation behind implementing the custom JSON importer has been the necessity which has risen since Eurostat recalibrated data quality in May 2017. In this process, the data which has been deemed as not meeting Eurostat's standards of quality has been disabled for viewing and download from both their interface as well as the web service. This information was obtained through direct communication with Eurostat's customer service.

Since data was downloaded into the local server before in the form of JSON files, a JSON importer was implemented to load the files into the database; for it to be processed by the loading layer.

4.4 Control modules

The main purpose of the controlling layer is to orchestrate data exchange between the View and Model layers. As described in previous sections, View is the user interface which not only represents data but is also used to interact with the user, sending feedback information to the control layer, which can then perform necessary operations on the model.

In this project, control layer has the following basic functionality:

- **Basic Data Loading** - the modules associated with primary data loading all have a common purpose of transforming the data from a database into View layer readable files that can then be visualized. The task of processing this data, however, is not as simple as transforming it from one format to another, but also includes performing macroeconomic mathematical calculations on the base data to obtain data relevant for inflation visualization. These operations are described in more detail in Section 4.5.

- **Data Editing** - Data from the existing base for the profile can be edited directly; a functionality already mentioned in previous sections, aimed at researchers that prefer direct access to data. The role of the controller layer in this aspect is first to gather data modified by the user in the interface provided, updating the data model with the custom data defined. Secondly, new series of graphs are visualized, backed by the newly established base data, whose purpose is to visualize the alterations made by the user.

- **Personalized Inflation Transformation** - similar to Data Editing layer, this module enables custom weight editing with the difference that the set of custom weights is a direct result of traversing the decision tree model built to gain insights into user's consumption patterns. The outcome of weight editing is producing an inflation graph that has both price indices, and custom weights as input. This custom graph represents the personalized inflation rate for the user broken down into COICOP categories.

4.5 Mathematical models

Mathematical models are used in the data loading process. During this procedure, data is extracted from the database stored locally, and transformed in 2 ways; firstly, mathematical models are applied on the data to ensure their macroeconomic validity and secondly, data is translated into JSON format for it to be visualized by the user interface.

When applying mathematical models to the data, following points should be considered

- Base data consists of HICP index [2] and the contributing weight of that category in the consumers' basket. For instance, category FOOD can have a HICP index 102.04 for June 2014 and contribution of 152.35 for the year 2014.

- Category weights describe to which extent does an inflation of a certain category contribute to the overall inflation rate. The weights are derived according to the product's importance in average household budgets. The weights are regularly updated using surveying the population, to obtain a national average expenditure of all types of consumers [1]. Taking into consideration that the sum of all weights should be 1000, reusing the example cited in the previous point, one could conclude that food and all the subcategories contained in it contribute 15,235% to the overall inflation.

- As mentioned, each category weight is determined by a yearly survey, implying that the weight values are calculated on a yearly basis. The problem is the difference between stacked contribution values and inflation values. They should be equal. However, they differ, because of the yearly weight basis. To smooth out the calculation of category contribution, weighted weights calculation has been implemented. Weighted weights calculation ensures that the months closer to the next year's weight estimation contain a weighted amount of the weight of the next or previous year, by calculating individual months' weights based on the weight values of previous 12 months. The approach is the following:
  - Firstly, the relative month needs to be determined, to understand how many months of the previous year need to be taken into consideration.
  - Secondly, the weight of the year in consideration needs to be multiplied with the month coefficient, which equals to the ordinal number of month to obtain this year's contribution to weight value.
  - Thirdly, the weight of the previous year needs to be multiplied by the year earlier coefficient to get last year's contribution to weight value.
  - Finally, the two contributions are summed, to obtain the weight value for the month in consideration.

  This model is best explained through an equation:

  $$w_{month} = (w_y * c * n) + w_{y-1} * c * (12 - n) ,$$

  where

  w_y - weight for the year in consideration

  w_{y-1} - weight for the previous year

  c - per-month coefficient, corresponding to a value of $\frac{1}{12}$

  n - ordinal number of the month (e.g. 3 for March)

- Automatic error detection and compensation is implemented as an integral part of data loading. This functionality aims to detect possible discrepancies between the total sum of all contributing categories in any contribution graph and the real value for CP00. As explained in this chapter, the overall inflation value can be broken down into categories which together form the overall inflation rate. Errors in precision when summing categories arise from the sheer number of categories involved in inflation contribution; for Austria, this number was 789 in 2016 [3]. It is for this reason that the automatic error compensation is intended to compensate for these minor gaps, and it does so in the following way:
  - Initially, the sum of all contributing categories per date is calculated.
  - Secondly, the amount of all contributing categories is subtracted from the CP00 value for each date.

– Thirdly, the weights are used to split the residual into parts whose number corresponds to the number of categories.

– Finally, each residual per category is added to the contribution of that category to the overall inflation. Now the sum of contributing categories will equal the overall inflation rate as specified in CP00.

This model is best explained through a system of equations:

$$\epsilon_t = \pi_{CP00} - \sum_{n=1}^{c} \pi_{t\,n}^{c}$$
$$\epsilon_t^c = \epsilon_t * w^c$$
$$\pi_t^c = \pi_t^c + \epsilon_t^c \,,$$

where

π_{CP00} - Total inflation rate

$\sum_{n=1}^{c} \pi_{t\,n}^{c}$ - Sum of all values of contributing categories

ϵ_t - Total Residual

w^c - Weight of category

ϵ_t^c - Residual of category

π_t^c - Calculated inflation rate of category

n - Time point

Taking these points into consideration, the contribution rate for individual categories is therefore calculated as such

$$\pi_{category} = (\frac{HICP^1_{category}}{HICP^2_{category}} * 100 - 100) * \frac{w_{category}}{\sum w_{allcategories}} \quad ,$$

where

$HICP^1_{category}$ - category HICP indicator for the considered month

$HICP^1_{category}$ - category HICP indicator for the considered month a year earlier

$w_{category}$ - category weight for the considered year

$\sum w_{allcategories}$ - sum of all category weights for the considered year. Should amount to 1000.

CHAPTER 5

Results

Since the original scope of this thesis is linking a data set which approximates yearly consumption of Austrian households with the concept of estimating a personalized inflation rate for a new one, a model needed to be built which is then used for this estimation. This chapter focuses on presenting the results of the evaluation of various models and their comparison, undertaken using methods presented in Chapter 3. Furthermore, the aim is to showcase the reasoning for their conceptualization, implementation, and evaluation. In this regard, Microsoft Azure Machine Learning Studio and Clus software were chosen for model building and assessment. Descriptive statistics calculated for these models in each of these tools were then compiled in a spreadsheet, along with an additional calculation of Mean Absolute Proportional Error (MAPE) measure of prediction accuracy as a universal method for comparing regression models across different tools. MAPE is widely accepted and popularized because of its straightforward interpretation and it is as such an excellent alternative to mean squared error [171]. The results are displayed in the next sections in a tabular form, and results are rounded to six decimal places.

Therefore, the first section focuses on analyzing the approach to model building, and the reasoning behind selected machine learning algorithms, along with providing information on the statistical measurements used. Subsequent sections will elaborate on the paradigm used for each of those algorithms, along with their prediction results. The chapter will close with a summary of results.

5.1 General approach to model building

Before approaching the model building, it is important to describe the data set in question briefly. As highlighted in Chapter 3, the data set used for model building is composed of 696 variables and 7162 data points, representing surveyed individuals. Out of 696 variables, 148 are categorical, and the rest is continuous, indicating expenditure for individual consumption categories. Data were normalized to reflect expenditure weights rather than the absolute values for each subcategory; but most importantly, for the 12 COICOP categories indicating their expenditure weights. Some of the descriptive variables were excluded; such as the household weight or household id, because of their insignificance in the overall prediction, but also to avoid spurious correlation that might occur while using these variables. Moreover, some consumption categories such as "Food" have been excluded as well, to include lower level subcategories in the prediction model to ensure that specific consumption categories are analyzed, leading to more specific questions asked to the end user. In other words, questions such as "Do you eat meat?" are far more specific and easier to answer than "Is your monthly expenditure on food greater than 300 Euro?" [126].

The primary goal of model building is to forecast the values of those 12 weights.

As described in Chapter 3, the choice of machine learning algorithms was heavily influenced by the fact that the output of the model needed to be in a decision tree-like structure. This is attributed to one of the most prominent requirements behind building the Personalized Inflation Calculator artifact, that of asking users simple binary questions which are easier to interpret and respond [123], assuming that this will make their responses more accurate than asking them to estimate their consumption patterns. An alternative approach would be to consider the input provided by users is relatively accurate, which would enable this research to use a variety of other machine learning algorithms. This topic is discussed in Chapter 6.

Decision trees were tipped as optimal algorithms for the task. Further analysis and evaluation of available decision tree algorithms and their compatibility with the data set at hand, yielded the selection of three possible algorithms to be used for building models; Univariate Decision Tree Regression, Univariate Decision Tree Classification and Multivariate Decision Tree Regression.

The Univariate Decision Tree Regression [172] algorithm regresses on a single target variable; so it is inapplicable in the context of forecasting 12 COICOP category weights. However, building 12 separate models, each using the Univariate decision tree algorithm on a subset of data contributing to the overall expenditure of their category plus the demographic data seemed like a plausible paradigm.

The Univariate Decision Tree Classification classifies a single target variable. The idea behind using this algorithm was to first organize all consumption data into clusters, assigning them a class label. The clustered data set is then used to train a Univariate Decision Tree Classification model to predict the class to which a new user would be assigned.

The Multivariate Decision Tree Regression [125][173] builds a model targeting multiple variables, so it seemed suitable for the task at hand; as it allows the building of a single model which includes all the descriptive variables to forecast the 12 COICOP consumption weights.

The sections below describe the tool choice in more detail and elaborate on results for each of these algorithms. Each section will present results of evaluating individual algorithms with and without data binning, as described in Chapter 3.

5.1.1 Statistical measurements used

This section will list the statistical measurements applied to compare algorithms employed in the model building process. Because the decision tree algorithms used, as recorded in Section 5.1, are either classification- or regression-based, their precision measurement differs as well.

Because of this reason, following precision measurement are utilized for regression models:

- **Mean Absolute Error (MAE)** - MAE calculation comprises of summing up the absolute values of errors e_i, only to divide it by the number of observed samples N [147]. It can be expressed like this:

$$MAE = N^{-1} \sum_{i=1}^{N} |e_i|$$

- **Category Weight** - represents the extent to which a certain category contributes to the average consumer basket.
- **Mean Absolute Proportional Error (MAPE)** - as mentioned in Section 5.1, MAPE is often used in practice because of its intuitive interpretation in terms of relative error [174][171]. Its calculation is fairly straightforward:

$$MAPE_g = \frac{1}{N} \sum_{i=1}^{N} |\frac{g(x_i) - y_i}{y_i}| \, ,$$

  where x_i denotes the i-th observation of the explanatory value, y_i is the ith observation of the target variable and g is a regression model.

Similarly, following precision measurement are used for classification models:

- **Overall accuracy** is measured as the number of positive class predictions, or true positives (TP) from all predictions made for all classes, where N is the total number of samples [175]:

$$A = \frac{TP}{N}$$

- **Micro-Averaged precision** is calculated by dividing up individual true positives TP, with the sum of TP and false positives FP of different data sets [175]:

$$P_k = \frac{TP_k}{TP_k + FP_k}$$

- **Micro-Averaged recall** is calculated by summing up individual true positives TP, false negatives FN of different data sets [175]:

$$P_k = \frac{TP_k}{TP_k + FN_k}$$

5.2 Individual univariate regression models per consumption category

To implement this machine learning paradigm, Azure Machine Learning's Univariate Boosted Decision Tree Regression algorithm was chosen. It is a machine learning algorithm that combines classification and regression tree models and fits them together for improving precision [124]. Since this algorithm allows targeting a single variable, the paradigm was to build 12 models each targeting an individual consumption category. The data set, therefore, needed to be split into 12 instances, each containing explanatory variables that were subcategories of the particular COICOP category. For this reason, "Select Columns in Dataset" modules were used, before splitting the dataset data points into 90% used for training, and 10% used for evaluation. The trained model, trained by using default Azure settings, was then scored and evaluated using appropriate modules from Azure and the results of this assessment can be found in Table 5.1.

Results differed when input data were binned into categories of highest and lowest 25%, as well as the middle 50% for each input variable. It can be observed that the average MAPE is slightly bigger, which is an expected result when binning data, and therefore decreasing the information contained in the descriptive variables [176].

COICOP Category[151]	**Mean Absolute Error**	**Category Weight**	**Mean Absolute Proportional Error**
Food and non-alcoholic beverages	0.1053	0.1316	0.8005
Alcoholic beverages, tobacco and narcotics	0.0198	0.0255	0.7765
Clothing and footwear	0.0366	0.0451	0.8112
Housing, water, electricity gas and other fuels	0.2319	0.2926	0.7924
Furnishings, equipment and routine maintenance of the house	0.0483	0.0599	0.8069
Health	0.0290	0.0373	0.7771
Transport	0.1021	0.8339	
Communication	0.0127	0.0152	0.8389
Recreation and culture	0.0874	0.1075	0.8124
Education	0.0081	0.0087	0.9357
Restaurants and hotels	0.0513	0.0651	0.7887
Miscellaneous goods and services	0.0696	0.0886	0.7860
Average	0.6668	0.0833	0.8026

Table 5.1: Evaluation of Univariate Decision Tree Regression without input data binning

COICOP Category[151]	**Mean Absolute Error**	**Category Weight**	**Mean Absolute Proportional Error**
Food and non-alcoholic beverages	0.1066	0.1316	0.8104
Alcoholic beverages, tobacco and narcotics	0.0218	0.0255	0.8538
Clothing and footwear	0.0375	0.0451	0.8326
Housing, water, electricity gas and other fuels	0.2353	0.2926	0.8040
Furnishings, equipment and routine maintenance of the house	0.0470	0.0599	0.7858
Health	0.0312	0.0373	0.8380
Transport	0.0941	0.1224	0.7685
Communication	0.0124	0.0152	0.8160
Recreation and culture	0.0869	0.1075	0.8081
Education	0.0067	0.0087	0.7730
Restaurants and hotels	0.0524	0.0651	0.8048
Miscellaneous goods and services	0.0711	0.0886	0.8030
Average	0.0669	0.8333	0.8036

Table 5.2: Evaluation of Univariate Decision Tree Regression with input data binning

5.3 Clustering and classification model

For the implementation of this paradigm, Multiclass Decision Forest in combination with K-Means clustering was used. The primary function of K-Means clustering was to clustering the consumption data into some classes, assigning a class label to each data point. After this classification has been performed, the machine learning algorithm was used on the initial data enriched with class labels, to forecast the consumption class.

Because only a single class is forecasted, the precision measurement focuses on evaluating the precision of predicting class label, and not individual COICOP categories. The evaluation of this method shall, therefore, focus on these parameters. Table 5.4 shows evaluation performed for 20, 50 and 100 centroids as a parameter input to K-Means algorithm. When training the model default Azure settings were used, and K-Means++ module provided was used for the clustering.

The overall accuracy experiences a significant drop with binned values, as shown in Table 5.4.

Number of centroids	**Overall accuracy**	**Micro-averaged precision**	**Micro-averaged recall**
20	0.5874	0.5874	0.5874
50	0.0069	0.0069	0.0069
100	0.0069	0.0069	0.0069

Table 5.3: Evaluation of Univariate Decision Tree Classification without input data binning

Number of centroids	**Overall accuracy**	**Micro-averaged precision**	**Micro-averaged recall**
20	0.3146	0.3146	0.3146
50	0.0279	0.0279	0.0279
100	0.0139	0.0139	0.0139

Table 5.4: Evaluation of Univariate Decision Tree Classification with input data binning

5.4 Single multivariate regression model for consumption categories

Multivariate regression, also called Multi-target, Multi-response or Multi-output regression aims to predict multiple target variables by constructing a single model [125] simultaneously. This functionality has proven itself ideal for the problem at hand, as the aim is to predict 12 COICOP category values based on the consumption data set used to train the machine learning model.

An initial search for an appropriate tool resulted in a surprisingly low level of open source machine learning libraries providing support for this algorithm. The most prominent ones found were R's mvpart package and Clus. Since mvpart package was removed from R's CRAN repository as deprecated, and some research papers leveraged Clus system for their multivariate regression problematic, reporting good experiences with both precision and usability [127][173], Clus has been chosen as the tool to construct the models at hand.

5.4.1 Tree depth analysis with Hold-out validation

One of the settings relevant for modeling the tree is the maximum tree depth. This measure determines the maximum nodes that can be iterated vertically to reach the leaf node, and thus also represent the maximum number of questions that might be asked to calculate personal consumption pattern. Tables 5.5 and 5.6 show the evaluation results with and without binning input data, setting the maximum tree depth to 10 and test set to 10% of the overall data set, keeping other Clus settings to default [37].

Maximum depth was also investigated for both tree versions. Tables 5.7 and 5.8 show the evaluation results for maximum depths of both binned and continuous data. The maximum depth for binned data was found to be 26, and 33 for continuous data respectively. Again, the test set was set to 10% of the overall data set, keeping other Clus settings to default.

COICOP Category[151]	**Mean Absolute Error**	**Category Weight**	**Mean Absolute Proportional Error**
Food and non-alcoholic beverages	0.055	0.1316	0.4178
Alcoholic beverages, tobacco and narcotics	0.0181	0.0255	0.7082
Clothing and footwear	0.027	0.0451	0.5983
Housing, water, electricity gas and other fuels	0.0907	0.2926	0.3098
Furnishings, equipment and routine maintenance of the house	0.0422	0.0599	0.7044
Health hline Transport	0.0288 0.0572	0.0373 0.1224	0.7716 0.4670
Communication	0.0103	0.0152	0.6762
Recreation and culture	0.0543	0.1075	0.5046
Education	0.0133	0.0087	1.5191
Restaurants and hotels	0.0295	0.0651	0.4529
Miscellaneous goods and services	0.0403	0.0886	0.4546
Average	0.0388	0.0833	0.4667

Table 5.5: Evaluation of Multivariate Decision Tree Regression without input data binning, maximum tree depth 10, for Hold-out validation

COICOP Category[151]	**Mean Absolute Error**	**Category Weight**	**Mean Absolute Proportional Error**
Food and non-alcoholic beverages	0.0488	0.1316	0.3707
Alcoholic beverages, tobacco and narcotics	0.025	0.0255	0.9782
Clothing and footwear	0.0343	0.0451	0.7601
Housing, water, electricity gas and other fuels	0.0869	0.2926	0.2969
Furnishings, equipment and routine maintenance of the house	0.045	0.0599	0.7512
Health	0.0314	0.0373	0.8413
Transport	0.0666	0.1224	0.5438
Communication	0.0153	0.0152	1.0045
Recreation and culture	0.0681	0.1075	0.6329
Education	0.0122	0.0087	1.3935
Restaurants and hotels	0.0404	0.0651	0.6202
Miscellaneous goods and services	0.0463	0.0886	0.5223
Average	0.0433	0.0833	0.5203

Table 5.6: Evaluation of Multivariate Decision Tree Regression with input data binning, maximum tree depth 10, for Hold-out validation

COICOP Category[151]	**Mean Absolute Error**	**Category Weight**	**Mean Absolute Proportional Error**
Food and non-alcoholic beverages	0.0529	0.1316	0.4019
Alcoholic beverages, tobacco and narcotics	0.0183	0.0255	0.7160
Clothing and footwear	0.0267	0.0451	0.5917
Housing, water, electricity gas and other fuels	0.0919	0.2926	0.3139
Furnishings, equipment and routine maintenance of the house	0.0427	0.0599	0.7128
Health	0.0295	0.0373	0.7904
Transport	0.0526	0.1224	0.4295
Communication	0.0112	0.0152	0.7353
Recreation and culture	0.058	0.1075	0.5390
Education	0.0124	0.0087	1.4163
Restaurants and hotels	0.0319	0.0651	0.4897
Miscellaneous goods and services	0.0416	0.0886	0.4693
Average	0.0391	0.0833	0.4697

Table 5.7: Evaluation of Multivariate Decision Tree Regression without input data binning, maximum tree depth 33, for Hold-out validation

COICOP Category[151]	**Mean Absolute Error**	**Category Weight**	**Mean Absolute Proportional Error**
Food and non-alcoholic beverages	0.0547	0.1316	0.4156
Alcoholic beverages, tobacco and narcotics	0.0229	0.0255	0.8960
Clothing and footwear	0.034	0.0451	0.7535
Housing, water, electricity gas and other fuels	0.1018	0.2926	0.3478
Furnishings, equipment and routine maintenance of the house	0.0536	0.0599	0.8948
Health	0.0379	0.0373	1.0154
Transport	0.07	0.1224	0.5715
Communication	0.0129	0.0152	0.8469
Recreation and culture	0.0659	0.1075	0.6125
Education	0.0151	0.0087	1.7247
Restaurants and hotels	0.0342	0.0651	0.5250
Miscellaneous goods and services	0.0593	0.0886	0.6690
Average	0.0468	0.0833	0.5623

Table 5.8: Evaluation of Multivariate Decision Tree Regression with input data binning, maximum tree depth 26, for Hold-out validation

The relationship between tree depth and Average Mean Absolute Proportional Error for all 12 categories were investigated. As it can be seen from Graphs 5.2, the Mean Absolute Proportional Error (MAPE) of the Test set decreases with the maximum tree depth up to depth 10, where it slightly increases as the depth of the tree increases for the dataset with data binning. Graph 5.1 indeed shows that the training MAPE decreases significantly for the dataset with data binning as tree depth goes beyond 10. This behavior coincides with the expectation that increasing maximum tree depth allows the algorithm to build a more complex model, which exhibits a lower error rate for the training model, but overfits [177] it at a certain point. Indeed, by combining graphs 5.1 and 5.2 overfitting can be observed, as the MAPE for trained model decreases with increasing depth, whereas the opposite shows for the test model, indicating the model's tendency to overfit the training data, resulting in reduced performance when confronted with test data points. Finally, there is a difference to the maximum depth of trees between the binned and continuous data model, attributed to the fact that continuous variables have a more significant number of interdependencies which need to be included in the model.

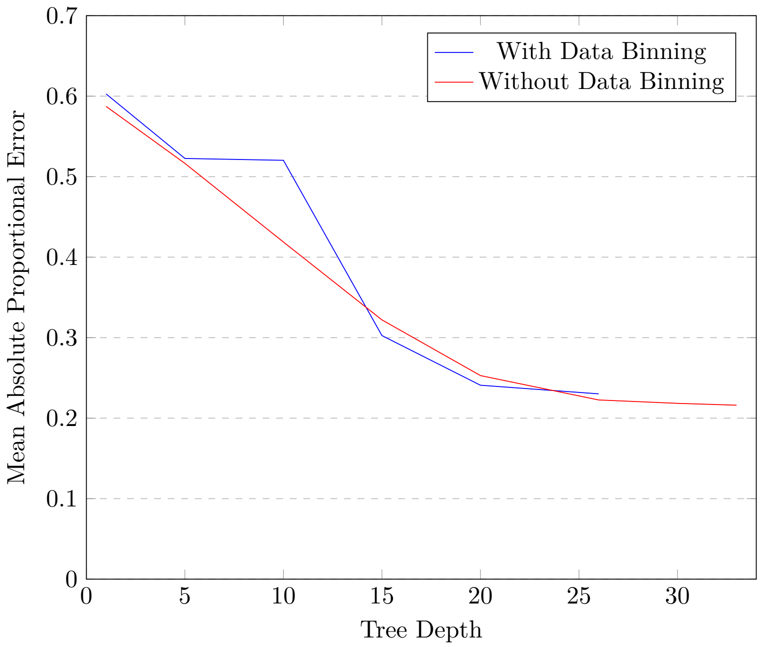


Figure 5.1: Average Training set Mean Absolute Proportional Error's relation to maximum tree depth for Hold-out validation

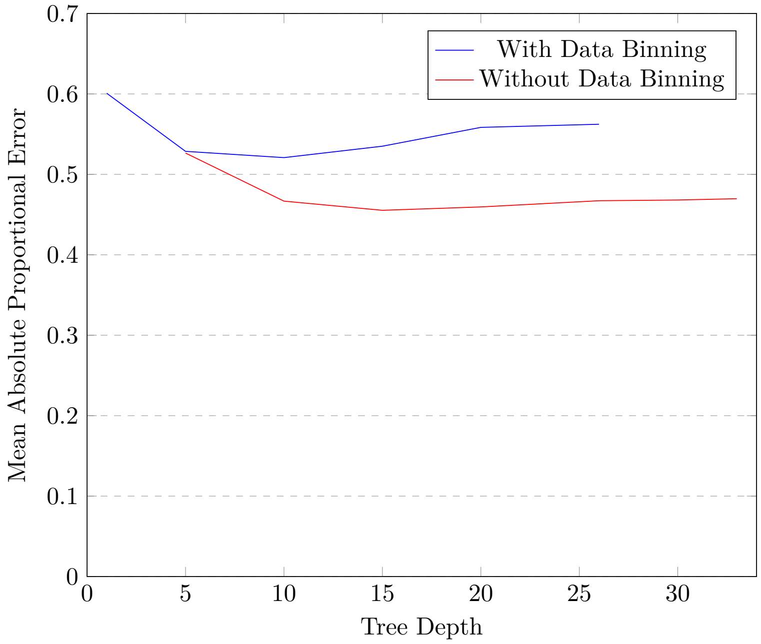


Figure 5.2: Average Test Set Mean Absolute Proportional Error's relation to maximum tree depth for Hold-out validation

5.4.2 Tree depth analysis with K-fold cross-validation

Another method used for constructing and evaluating a model is K-fold cross-validation. The latter is a method which divides the set into k of disjoint sub data sets, and then uses k-1 of them to train the model, and one of the sub data sets to test the model [178]. For this evaluation, k of 10 has been used.

Table 5.9 show the final results of evaluating the K-fold cross-validation algorithm on binned data; comparing these results with the Hold-out evaluation prove a better performance by the former algorithm, with an optimal maximum tree depth of 10. Moreover, Figure 5.3 displays a relationship between MAPE for binned and continuous data using K-fold cross-validation. The link is in every way similar to the one using Hold-out evaluation, with minor differences in MAPE per COICOP categories exhibited.

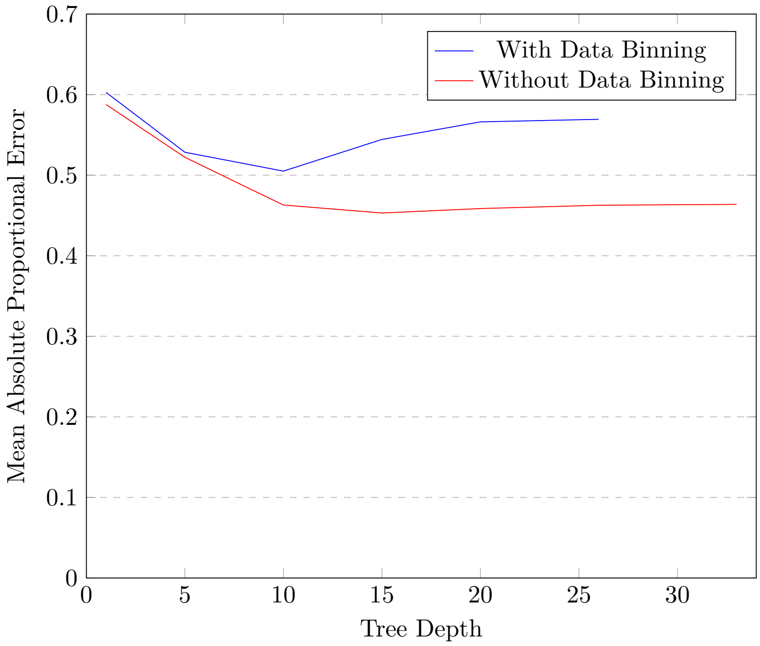


Figure 5.3: Average Test Set Mean Absolute Proportional Error's relation to maximum tree depth for K-fold cross-validation

COICOP Category[151]	**Mean Absolute Error**	**Category Weight**	**Mean Absolute Proportional Error**
Food and non-alcoholic beverages	0.0502	0.1316	0.3814
Alcoholic beverages, tobacco and narcotics	0.0206	0.0255	0.8060
Clothing and footwear	0.0301	0.0451	0.6670
Housing, water, electricity gas and other fuels	0.0921	0.2926	0.3146
Furnishings, equipment and routine maintenance of the house	0.0476	0.0599	0.7946
Health	0.0339	0.0373	0.9083
Transport	0.065	0.1224	0.5307
Communication	0.0105	0.0152	0.6894
Recreation and culture	0.0587	0.1075	0.5455
Education	0.0139	0.0087	1.5876
Restaurants and hotels	0.0319	0.0651	0.4897
Miscellaneous goods and services	0.0506	0.0886	0.5708
Average	0.0420	0.0833	0.5051

Table 5.9: Evaluation of Multivariate Decision Tree Regression with input data binning, maximum tree depth 10, for K-fold cross-validation

Decision tree pruning

As exhibited in the previous sections, both Hold-out and K-fold validation techniques share a common issue which is overfitting the model. To combat this problem and minimize prediction errors, Decision Tree Pruning was used during the development of predictive models. As described in work by Mehda et al. [179], decision tree pruning has a goal of removing tree nodes which do not provide enough power to classify instances. Although it simplifies the model, making it intuitively less potent for predictions, at the same time it removes complexity introduced by overfitting the model on the training set, thus reducing error when predicting the values for new instances. For the data set at hand, this means that models with deeper maximum depths can be explored, counting on Decision Tree Pruning to reduce errors associated with overfitting the model.

This hypothesis was further boosted by works of Weiss and Indrukhya [180], that found that using stratified ten-fold cross-validation to choose the number of pruning yields unbiased trees [178], but also Breimann et al. [146] that confirmed the hypothesis in their research. Table 5.10 shows the results of this experiment, which resulted in finding that maximum tree depth 20 to be the overall best performer.

5.5 Model selection and evaluation using Personal inflation calculator

The model selected, a pruned multivariate Decision tree with maximum depth 20, using K-fold cross-validation method with binned input data, was chosen both because it satisfies the criteria set for input data, as well as the best performance among methods evaluated as part of this work.

This model was then used to evaluate randomly chosen 100 individuals from the consumer survey. The summary of this evaluation are showcased in Table 5.11.

COICOP Category[151]	**Mean Absolute Error**	**Category Weight**	**Mean Absolute Proportional Error**
Food and non-alcoholic beverages	0.0501	0.1316	0.3806
Alcoholic beverages, tobacco and narcotics	0.0213	0.0255	0.8334
Clothing and footwear	0.0287	0.0451	0.6360
Housing, water, electricity gas and other fuels	0.0892	0.2926	0.3042
Furnishings, equipment and routine maintenance of the house	0.0475	0.0599	0.7929
Health	0.0337	0.0373	0.9029
Transport	0.066	0.1224	0.5389
Communication	0.0099	0.0152	0.6500
Recreation and culture	0.0577	0.1075	0.5362
Education	0.0136	0.0087	1.5534
Restaurants and hotels	0.0308	0.0651	0.4728
Miscellaneous goods and services	0.0487	0.0886	0.5494
Average	0.0414	0.0833	0.4972

Table 5.10: Evaluation of Pruned Multivariate Decision Tree Regression with input data binning, maximum tree depth 20, for K-fold cross-validation

COICOP Category[151]	**Mean Absolute Proportional Error**	**Standard Deviation**	**Category Weight**
Food and non-alcoholic beverages	0.3922	0.0449	0.1316
Alcoholic beverages, tobacco and narcotics	0.8150	0.0216	0.0255
Clothing and footwear	0.7132	0.0379	0.0451
Housing, water, electricity gas and other fuels	0.3314	0.0809	0.2926
Furnishings, equipment and routine maintenance of the house	0.7378	0.0577	0.0599
Health	0.9026	0.0525	0.0373
Transport	0.6073	0.0760	0.1224
Communication	0.7007	0.0116	0.0152
Recreation and culture	0.5294	0.0464	0.1075
Education	1.5408	0.0189	0.0087
Restaurants and hotels	0.5696	0.0446	0.0651
Miscellaneous goods and services	0.6375	0.0621	0.0886
Average	0.7065	0.0463	0.0833

Table 5.11: Evaluation for random 100 data points of the entire set, using Pruned Multivariate Decision Tree Regression with input data binning, maximum tree depth 20, for K-fold cross-validation

5.6 Results summary

This chapter has showcased various decision tree model building methods, as well as their performance on the data set used for this work. As described in Chapter 3, the goal of this work was to construct a tree-like model that predicts weight values for 12 COICOP categories. Although there might be more appropriate machine learning algorithms for the task of predicting the 12 weight values, the decision of constructing decision trees was taken mostly because a such a model can be easily translated to a user interface, to obtain input from new users. Furthermore, because of the binary nature of each split in the tree, interacting with the user is simplified as it reduces to a series of simple "yes or no" questions.

Algorithm selection yielded three methods; Univariate Decision Tree Regression targeting individual category weights, Univariate Decision Tree Classification attempting to cluster and classify data points into clusters and Multivariate Decision Tree Regression. The three methods were put in comparison, and their behavior while changing control parameters was observed.

Since Multivariate Decision Tree Regression has shown itself as best performing the algorithm, some more detailed variations in depth and validation methods were explored to observe model's behavior with the scope of finding the optimal set of parameters for training a model. The investigation has also shown the presence of overfitting for higher tree depths, because training set error reduced after a certain depth, whereas the error on unseen instances from the test set was increasing on higher tree depths.

Finally, tree pruning was used to remove parts of the tree that provide little power to the regression, to reduce overfitting. This has proven itself as the optimal trade-off between deepening the decision tree model and reducing the test set error induced by overfitting. Thus the optimal model was found, a pruned Multivariate Decision Tree of depth 20, evaluated using K-fold cross-validation.

CHAPTER 6

Conclusion

"Inflation is when you pay fifteen dollars for the ten-dollar haircut you used to get for five dollars when you had hair."

- Sam Ewing, *1982*

This chapter summarizes the outcomes of this work, referencing the research questions stated in Chapter 1. Furthermore, limitations of this thesis as well as future work are addressed.

6.1 Summary and main findings

This thesis focuses on inflation, one of the most prominent key economic indicators. It firstly analyzes what are the factors that make up the calculation of an inflation rate of a country, also identifying the key drivers of inflation perception among the general public. It starts with its general lack of positive image due to past experiences, to trace the causes of misperception of the key elements that make up inflation; personal expenditure and price dynamics.

The former holds relevance, as this work argues that the level of information a member of general public possesses on their expenditure is not sufficient to produce a correct personalized inflation estimation given the current state of the art. The purpose of this work is, therefore, to showcase an alternative approach to this calculation, which takes this hypothesis into account and can provide an estimation after a series of questions that are assumed to be easy to answer for an uninformed user.

Chapter 1 elaborates on the general relevance of inflation and its perception. Moreover, it sets a framework for the problems addressed in this thesis, as well as the importance and the method of an alternative approach to resolve the issue identified. The uninformed user hypothesis is stated in this chapter, as well as the way of circumventing the limitations that it implies. Chapter 2 provides a theoretical background on the topics addressed in this thesis. Firstly, information visualization is researched, most notably its capability of summarizing a complex set of information into a form easily understood also by non-experts. Secondly, the perception of macroeconomics is investigated, along with some data sources available to the general public. Thirdly, inflation as a key economic indicator is examined, initially providing a theoretical background on its state, followed by a state of the art research on inflation analysis sources available to the general public and rounded off by a study on personal inflation. The latter encompasses an overview of the relevance of this topic as well as research on the currently available personal inflation calculators and their modes of operation. The state of the art research laid out in this chapter was relevant not only to investigate where this study, along with the artifacts which it produced can be potentially placed within the research landscape but also insights and ideas which can be used within it.

Chapter 3 deals with the methodological approach to this research, describing the development and design methods behind it, along with the reasoning behind the creation of research artifacts. Since Design Science methodology was used, a necessary step to research an alternative method to estimating personal inflation rate was the creation of a model using machine learning methods. This also led to the definition of requirements that this research needed to satisfy to meet its research objectives. Furthermore, an interpretative framework which acts as a wrapper used to provide functional usability to its users was created as well. This chapter also touches upon the underlying data set used for the creation of this model, and valuable insights gathered during dataset analysis phase, as well as the justification behind transformation methods used to prepare the data set for model creation.

Chapter 4 describes the artifact implementation throughout the entire lifecycle. Initially, a stakeholder functionality adherence is described, also serving as a walkthrough for artifacts' usage. Technological architecture, along with data model and control modules is also described, providing insights on the artifacts' base components and the way they interact with the final product. Finally, Mathematical models used in the implementation are mentioned, namely the weighted weights and error compensation modules.

Chapter 5 provides an evaluation of the models conjured in the methodological phase of the thesis. It describes the steps which led to an objective assessment of the machine learning algorithm deemed as best suiting to the task at hand. Results of individual algorithm evaluation are presented in tabular and graph form. Methods and parameters were varied with an objective of finding optimal precision while satisfying requirements from in Chapter 3 and the research objective stated in Chapter 1. Summary of this chapter also concludes that within this boundaries, Multivariate Regression Decision tree with pruning and K-fold cross-validation has shown itself as an appropriate machine learning algorithm for the task.

6.2 Discussion

The central research question, finding an appropriate machine learning algorithm for an alternative approach to personal inflation calculation, has been answered in Chapter 5. Although these results are arguably limited, which will be touched upon in the limitations section of this chapter, the fact that this research gap has been addressed is beneficiary for personalized inflation research as a whole. Moreover, the process associated with researching the theoretical background of this topic yielded a fair overview of the entire subject, as well as its relevance in the global economy. The author of this work speculates that as global markets recover from the 2008 crisis, inflation is rising [181][182][183], and as such is back as a topic attractive to the general public.

A vital link made in this work is the one between malformed price dynamics perceptions and the lack of correct information general public has on their expenditure. As highlighted in Chapter 1, this is the basis for researching an alternative approach to personalized inflation modeling, leading ultimately to decision trees being chosen as machine learning algorithms suitable for the task. Finally, the model selected for the artifact implementation addresses this problem directly, as the questions asked do not require a high level of information provided by the user, but a "Yes" or "No" response instead.

The role of artifacts in potential educational purposes cannot be overlooked. Chapter 4 showcases examples of reasoning that can be performed to deduct conclusions on price dynamics on both macro and individual level. This adds to the arguments presented in Chapter 2 that there is indeed no dedicated tool for inflation analysis that might also be used in education.

The potential use results and artifacts provided by this work might have with the general public is still to be evaluated. The link between daily consumption and inflation is not often made by an average citizen, that associates inflation with something that should be avoided [7], as opposed to a significant indicator that often accompanies positive macroeconomic developments such as growth or reduced unemployment. The objective of making this tool accessible to the general public advocating its usage is addressed in Section 6.4.

6.3 Limitations

Prediction of accuracy is a definitive limitation of this work since an average MAPE of 0.4972 indicates that the model is still not in its mature phase. The most likely culprit for this level of precision is a high dimensional data set (689) compared to its number of data points (7163), which makes precise model building quite a challenging task.

Another problem faced during development of this thesis is a lack of possibility to compare evaluation to benchmark results. This is because data obtained from state of the art personalized inflation calculators are not available; but even if they were, their validity could not be verified as actual consumption data by individuals using those calculators are also unavailable for comparison. In fact, the only consumption data available is the Austrian Consumption Survey 2014/2015 used as data basis for building the model. An ideal situation would be to either track the actual consumption of users using the personal inflation tool or to have a subset of users that participated in the consumption survey use the personal inflation tool. Both of those options are not feasible. Lack of a benchmark to which results of estimating this model implies that the validity of this method cannot be evaluated versus state of the art personal inflation estimation methods.

Some of the conclusions, most notably Brachinger's prospect theory [13] on which the hypothesis of uninformed users is based have been criticized by Hoffmann et al. [30] as well as Aucremanne et al. [16] and Dohring and Mordonu [31], mostly for basing the estimations on arbitrary assumptions. For example, Dohring and Mordonu criticize Brachinger's decision to set a loss aversion exogenous parameter to 2, as it is based on theoretical and not empirical assumptions such as a survey measure or inflation perceptions. Hoffmann et al. challenge each of the hypotheses put forward by Brachinger, among which is a doubt cast on whether the frequency of purchases influences the perception consumers to have on how high the inflation rate is.

Application of this criticism on this work involves two aspects.

Firstly, choice of binning the consumption data in the survey has been made due to the assumption that providing simple input is within the range of possibilities of the user. That led to a decision tree being constructed that due to a binned data has decision points where answers can be placed in the range of few - average - lots instead of exact numbers. An alternative approach would be to leave data in a continuous format so that a decision tree is built which has split point based on the exact amount of expenditure. User would then not be asked whether they have, for example, "been on a holiday abroad this year for more than a week", but instead, the question would be something like whether they "have spent more than 700 EUR this year". The exact benefits of binning data cannot be evaluated, since, as already mentioned, a benchmark for comparison is absent.

Secondly, restricting the choice of machine learning algorithms to a Decision tree limited the number of algorithms that could have been used. The uninformed user hypothesis has led the author to Decision tree algorithms, but with this hypothesis out of the way, one might explore other means of constructing models that could estimate personalized inflation better.

Another limitation of this work is the Consumption Survey 2014/2015 dataset itself, which is conducted in 2 weeks and might therefore not encode information on durable goods just as well as FROOPP [184] purchases.

6.4 Future work

Future work will focus firstly on improving estimation precision. This might be achieved by either expanding the data set, including a previous consumption survey to build an upgraded model or by finding a more suitable machine learning algorithm, due to some of the limitations algorithms used have exhibited. Due to the ever-changing needs of an average consumer [185], the inclusion of an old consumption survey data set might include a coefficient which will make up for changes in consumption, to compensate for the lagging effects. Improvement on precision might also come from manual pruning of some attributes in the data set, by building up auxiliary decision trees which might focus on demographics of the user. In this way, building a decision forest which determines which tree to use based on demographic characteristics of a user might result in more accurate models. Creating subsets of those trees might be useful too, as certain consumption attributes might hold no relevance to some demographic groups.

Other potential work is associated directly with the artifacts of this thesis, which are accessible to the general public at the time of writing of this thesis. Creating a better user experience to attract more users might be interesting, as well as storing information on the usage. For instance, swipe confidence might be recorded, to find statistics which categories users feel most comfortable with, and which not. This would also imply that some feedback on how the questions are asked would be necessary, as that might create spurious correlation with the previously mentioned swipe confidence.

Finally, personal inflation calculator might be expanded to different countries, since a paradigm for data assimilation and model building is established with this thesis. The author of this work speculates that popularizing this tool might be beneficial to the international public since it allows them to analyze the price dynamics of their consumption. Hopefully, this might aid in raising awareness of what inflation is and how it can be leveraged for personal benefit.

List of figures

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