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Applied Data Science in the Pension Industry: A Survey and Outlook

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Abstract

The pension industry, much like the rest of the financial industry, is increasingly adopting data science and artificial intelligence-based solutions. Applications range from leaner and faster operations ("doing the same thing better") to completely new value propositions. However, the available literature suggests that the pension industry appears to be relatively conservative and cautious when it comes to adopting new and dynamically changing machine learning (ML) techniques. The black box nature of most ML techniques also appears to contribute to the skepticism of the pension sector. Hence, there seems to be a gap between the potential applications of data science solutions proposed by researchers and their application in the pension industry. This article provides (i) a review of what has been reported in the data science literature, (ii) a taxonomy of ML techniques that can be applied for challenges in the pension industry, and (iii) a categorization of the different aspects of the pension industry that are covered in state-of-the-art applied data science.

We surveyed 25 papers and presentations on the application of data science in the pension industry and highlight the major machine learning techniques that were used and their applicability in the pension sector. These techniques are concisely introduced to provide a basis for stakeholders to gain an understanding of their potential applicability to tackle challenges in the pension industry. Based on the existing research, three areas of the pension industry are identified as most relevant for the application of machine learning techniques: customer focus, organizational process optimization, and personnel optimization. Open issues and further opportunities regarding the application of data science in the pension sector are discussed.

We surveyed the existing body of literature to summarize how data science is being currently leveraged to deal with issues related to pensions. Prominent developments appear along the fronts of prediction and chatbot development. Our analysis suggests that there remains ample room in the pension industry to explore the use of other machine learning and data mining methodologies, such as clustering, natural language processing, and reinforcement learning. This includes gleaning insights from unconventional sources such as social media activity, and developing new customer-focused and business development applications.

Samenvatting
Toegepaste datawetenschap in de pensioensector: een overzicht en vooruitblik

De pensioensector maakt in toenemende mate gebruik van oplossingen die gebaseerd zijn op datawetenschap. Dit artikel geeft (i) een overzicht van wat hierover in de datawetenschapsliteratuur bekend is, (ii) een taxonomie van zelflerende technieken (machine learning)– die toegepast kunnen worden in de pensioensector en (iii) een categorisering van de verschillende aspecten van de pensioensector waarvoor de toegepaste state-of-the-art datawetenschap oplossingen biedt.

We hebben 25 artikelen onderzocht naar toepassingen van datawetenschap in de pensioensector. We belichten de belangrijkste machine learning-technieken die zijn gebruikt en bespreken hun inzetbaarheid in de pensioensector. Deze technieken worden kort voorgesteld en op basis van het bestaande onderzoek worden drie gebieden van de pensioensector geïdentificeerd die het meest kunnen profiteren van de toepassing van machine learning-technieken: klantgerichtheid, optimalisering van organisatorische processen en optimalisering van personeel. Openstaande vraagstukken en verdere mogelijke toepassingen van datawetenschap in de pensioensector worden besproken.

Uit onze analyse blijkt dat in de pensioensector nog veel ruimte is voor onderzoek naar de inzet van machine learning en datamining, zoals voor clustering, natuurlijke taalverwerking en ondersteund leren, om inzichten te verkrijgen vanuit onconventionele bronnen, bijvoorbeeld activiteiten op sociale media, en voor de ontwikkeling van nieuwe toepassingen op het gebied van klantgerichtheid en bedrijfsontwikkeling.

1. Introduction

It has been suggested that the pensions industry lags behind other financial sectors in its adoption of data science and artificial intelligence (AI) technologies, including machine learning and natural language processing[1], largely owing to a lack of expertise and focused strategic investment. Data science and AI offer new approaches in data analysis, optimization, and pattern recognition that could be applied to address long-standing pension challenges, and that could be the vehicles towards new commercial possibilities as well as support for individual decisions (Kaufmann et al. 2018). Automated processing of large data volumes may lead to more reliable and accurate predictive models (Talwar & Kumar 2013). The reliance of AI on data also requires a fundamental shift in corporate culture towards improvement in data management practices (McAfee & Brynjolfsson 2012).

The purpose of this article is to give an overview of current developments in the application of data science and artificial intelligence in the pension industry and related financial services.

The main contributions include:

1. An overview of how data science and AI are being applied to pension research and systems.
2. An examination of machine learning techniques that can be adopted for pension-based scenarios.
3. A discussion of open issues relating to the adoption of data science in the pension industry.

We surveyed 25 papers and presentations on the application of data science in the pension industry and highlight the major machine learning techniques that were presented in these papers as well as their applications. The main aspects of these techniques are introduced in this article and tagged with representative reference, presented in Table 1 below.

The rest of this article is organized as follows. The broad application of data science in the financial services industry is summarized in Section 2. Section 3 explores the taxonomy of applicable machine learning algorithms for the pensions industry. In Section 4 a literature review of data science research applied to the pension industry is provided. Section 5 highlights some open issues regarding the adoption of data science in the pension industry, and Section 6 provides concluding remarks.

1 *https://www.pensionsage.com/pa/images/PA_Oct_2018_AI.pdf*

2. Data Science in Financial Services

Machine learning has achieved remarkable success in many domains. Its potential has increased due to developments in new technologies such as neural networks. Examples of applicable data science solutions include advanced chatbots, identity verification in client onboarding (i.e, welcoming new clients), transaction data analysis, fraud detection in claims management, pricing in bond trading, price differentiation in car insurance, automated analysis of legal documents, customer relation management, risk management, portfolio management, trading execution, and investment operations. The pension industry still has a lot of room to capitalize on the benefits of machine learning and data science. This paper highlights the ground already covered by researchers, by reviewing the literature on the data science approaches that have been applied in the pension domain. As such it illustrates to industry professionals what can be achieved and provides an overview for interested researchers.

Many machine learning algorithms operate in real time and update as new data are entered, which fits well with challenges in financial services such as portfolio management and stock market prediction. In other domains, platforms such as Amazon and Netflix predict in real time the preferences of their customers based on previous choices (Bell et al. 2008); this could also be applied to customers in the pensions industry. Models for prediction of weather changes also update continuously online as environmental conditions change (Alavi et al. 2016); they can be applied for pricing in bond trading and the like. The accuracy of these models is the result of the training process and automation that are part of machine learning. Within the financial sector, machine learning algorithms such as decision tree and neural networks have been used to detect credit card fraud. These algorithms help companies to minimize the losses from such financial crime. In addition, when coupled with a real time system, this method can quickly inform clients and rapidly resolve problems (Bolton & Hand 2001, Delamaire et al. 2009, Juszczak et al. 2008, Pozzolo et al. 2014). Studies in the insurance sector have used artificial neural networks to evaluate the financial capability of insurance companies and to predict insolvency (Olaniyi et al. 2012). Other studies have used feedforward neural networks with the back-propagation algorithm to build decision models for five insurance categories including life, annuity, health, accident, and investment-oriented insurance (Lin et al. 2008). Machine learning algorithms also have been used to analyze the quality of mortality models (Deprez et al. 2017). Bacham & Zhao (2017) analyzed the performance of a set of machine learning methods in assessing credit risk of small and medium-sized borrowers, with Moody's

Analytics RiskCalc model serving as the benchmark model. We elaborate on how to use data science in the next section by providing an in-depth description of the various learning techniques and providing examples of where they can be applied.

Econometrics and machine learning models

Econometrics and ML models both apply statistical methods to make inferences on data. However, according to Frisch (1933) in the very first issue of *Econometrica*, econometrics is about "economic theory in its relation to statistics and mathematics". The main purpose of econometrics is not to predict but to quantify an economic phenomenon. Thus, econometric models often test hypotheses based on economic theory or game theory and make assumptions about the data investigated. On the contrary, data science and machine learning are driven by data rather than theory, not making any assumptions on the data. Thus, the most important difference between classical econometric models and ML is that the former focus on estimation and the testing of hypotheses, often in smaller samples, whereas the latter focuses on the best functional approximation, often in huge samples. Moreover, econometric modeling mostly focuses on parametric methods making distributional assumptions, ML more often (but not exclusively) applies non-parametric distribution-free methods.

3. Learning Techniques

Machine learning is a subfield of computer science. It is a type of Artificial Intelligence (AI) that uses historical data as input to predict new output values. It uses machines to enable learning with new information without the need to rewrite the program. Machine learning evolved from pattern recognition and computational learning theory. Here we elaborate on some essential concepts of machine learning as well as on frequently applied machine learning algorithms for smart data analysis.

A learning algorithm takes a set of samples as input. This is called a training set. In general, there are four main learning categories: supervised, unsupervised, semi-supervised, and reinforcement learning (Bishop, 2006; Barber, 2012; Murphy, 2012). In supervised learning, the training set consists of samples of input variables together with a target variable of interest, also known as labels. In unsupervised learning, no labels are required for the training set. Semi-supervised learning deals with the case of having a small number of labels for some of the samples in the training set while most labels are missing.

Reinforcement learning (RL) deals with the problem of learning the appropriate action or sequence of actions to be taken for a given situation to maximize payoff. According to Snow (2019), reinforcement learning in finance comprises the use of an agent that learns how to take actions in an environment to maximize some notion of cumulative reward. The agent exists in a predefined environment and receives as input the current state and is then asked to take an action to receive a reward, the information of which can be used to identify the next optimal action. The benefit of reinforcement learning algorithms is that the final objective function can be the realized/unrealized profit and loss, but also values like the Sharpe Ratio, maximum drawdown, and value at risk measures. RL allows for end-to-end optimization[2] on what maximizes rewards. The RL algorithm directly learns a policy. For instance, reinforcement learning answers the question, "Should I buy the asset today?", whereas supervised learning answers the question, "Will the price of the asset increase tomorrow?". Thus, reinforcement learning algorithms lend themselves well for developing trading strategies.

This paper focuses on supervised and unsupervised learning, since they have been and continue to be widely applied in the financial services industry. The highlighted machine learning models are the most prominently used data science models in the

2 End-to-end optimization entails the optimization process over a system or service from beginning to end until the delivery of a complete functional solution.

pension industry. The objective of supervised learning is to learn how to predict the appropriate output variable for given input variables. Applications where the target labels consist of a finite number of discrete categories are known as classification tasks. If the dependent variables are text-based, the aim is to determine whether the text leans towards positive or negative classification; this is called sentiment analysis. Cases where the target labels are comprised of one or more continuous variables are known as regression tasks (Bengio et al. 2016).

Defining the objective of unsupervised learning is more difficult. One of the major objectives is to identify viable clusters of similar samples within the input data; this is known as clustering. The objective may also be to discover a useful internal representation of the input data by pre-processing the original input variable in order to transfer it into a new variable space. This pre-processing stage can significantly improve the result of the subsequent machine learning algorithm. Bishop (2006) aptly calls it feature extraction.

3.1 Supervised Learning Techniques

Linear regression

Linear regression is a method that is used to model the linear relationship between a dependent variable (target) and one or more independent variables (predictors). It is based on the statistical ordinary least squares (OLS) method, where the model is fit such that the sum-of-squares of differences of observed and predicted values is minimized. The error function is minimized as an optimization function to estimate the coefficients (*bi*). To avoid overfitting, this can be further developed to include a regularization term in the optimization function. Overfitting happens when the model captures the noise in the training dataset. By noise we mean the data points

$$\textit{observed data} \rightarrow \quad y = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_p x_p + \varepsilon$$

$$\textit{predicted data} \rightarrow \quad y' = b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_p x_p$$

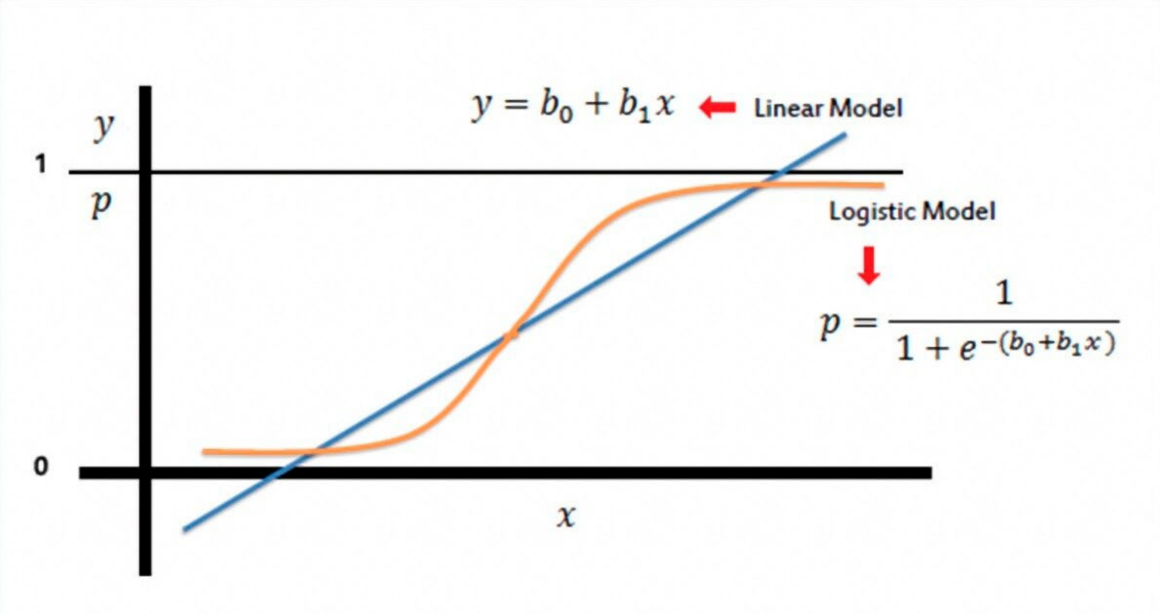
$$\textit{error} \rightarrow \quad \varepsilon = y - y'$$

$$\textit{minimize} \sum (y - y')^2 \qquad \text{OLS}$$

$$\textit{minimize} \sum (y - y')^2 + \lambda \sum |b| \qquad \text{Lasso}$$

$$\textit{minimize} \sum (y - y')^2 + \lambda \sum b^2 \qquad \text{Ridge}$$

Figure 1 Logistic regression (Sayad, 2012)



that do not really represent the true properties of the data, but instead chance. A regularizer shrinks the coefficient estimates towards zero to mitigate overfitting and, thereby, low accuracy of the model. When the regularizer is based on the so-called L1-normalization of the coefficients, it is referred to as Lasso regression. When the regularizer is based on the so-called L2-normalization of the coefficients, it is called a Ridge regression.

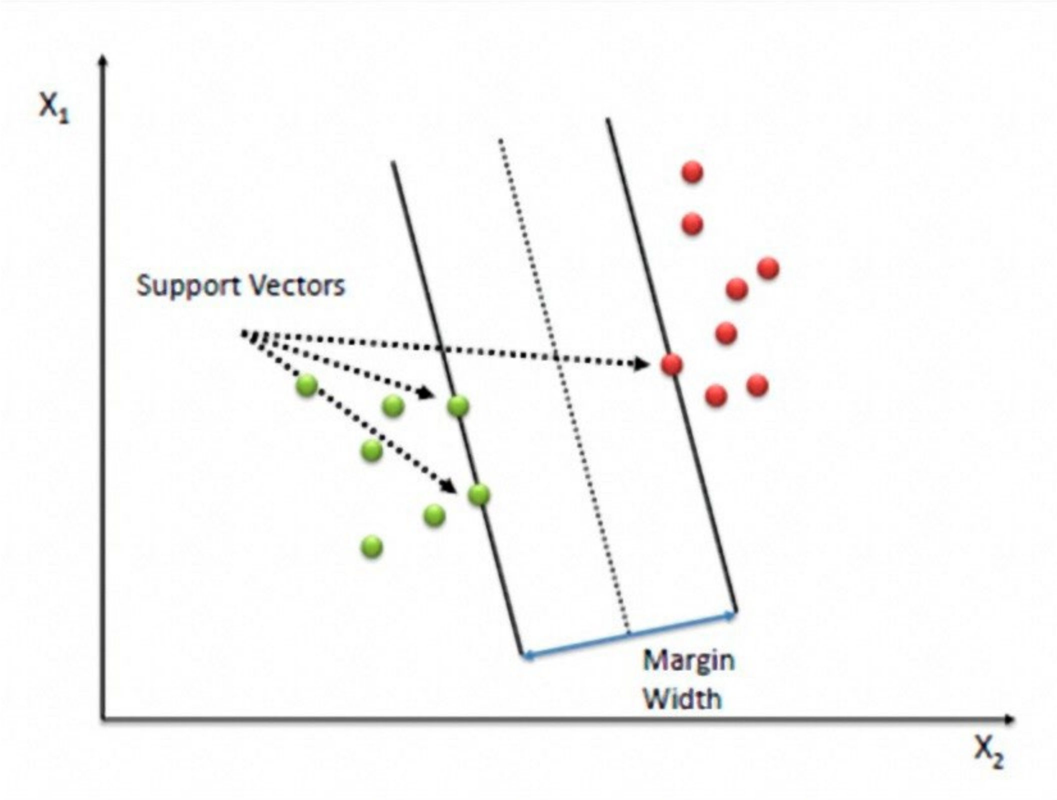
Logistic regression

A logistic regression predicts the probability of an outcome that can only have two values (i.e. a binary variable). A logistic regression produces a logistic curve as depicted in Figure 1, which is limited to values between 0 and 1. The curve is constructed using the natural logarithm of the "odds" of the target variable, rather than the probability (Hosmer Jr et al., 2013). Moreover, the predictors do not have to be normally distributed or have equal variance in each group. Figure 1, taken from Sayad (2012), shows an example of a logistic curve in comparison with a linear regression.

Support vector machines

Support Vector Machines (SVM) perform classification by representing the predictor variable space in a higher dimensional variable space. This is achieved through mathematical transformation of the variables and finding the separating hyperplane that maximizes the margin between the two classes. The vectors (cases) that define the hyperplane are the support vectors (Cortes & Vapnik, 1995). Figure 2, taken from Sayad

Figure 2 Support vector machine (Sayad, 2012)

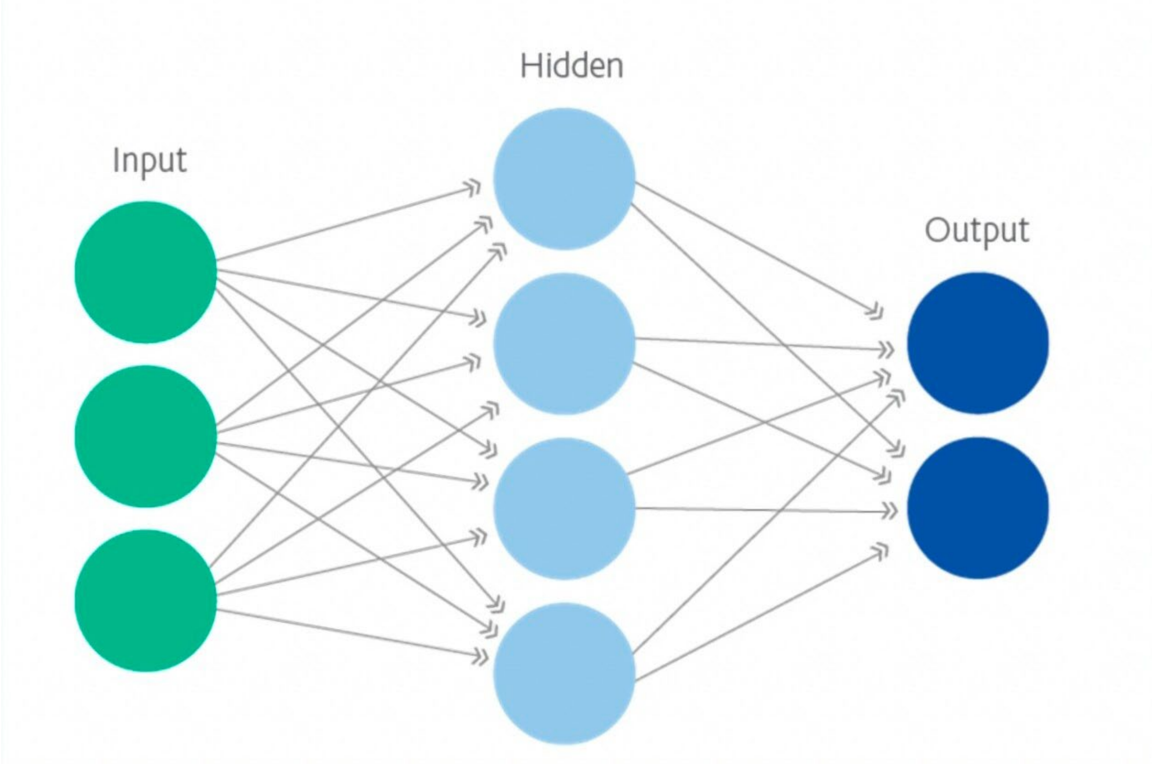


(2012), shows an example of support vectors on a linearly separable variable space for hypothetical observation data. In the figure the dotted line without arrowhead is the line that linearly separates different classes of the data points. The line is computed such that it maximizes the minimum distance between data points; these data points are called support vectors (see Figure 2). SVM differs from the other classification algorithms in that it chooses the decision boundary that maximizes the distance from the nearest data points of all classes. SVM does not merely find a random decision boundary; it finds the optimal decision boundary.

Artificial neural networks

An artificial neural network (ANN) is a mathematical simulation of a biological neural network. Its simple form is shown in Figure 3 (see Bacham & Zhao, 2017). In this example, there are three input values and two output values. An ANN consists of a network of artificial neurons (also known as "nodes"). These nodes are connected to each other, and to these connections values are assigned reflecting their strength: inhibition (maximum −1.0) or excitation (maximum +1.0). If the absolute value of the connection is high, then it indicates a strong connection. Different transformations

Figure 3 Artificial Neural Network (Bacham & Zhao, 2017)



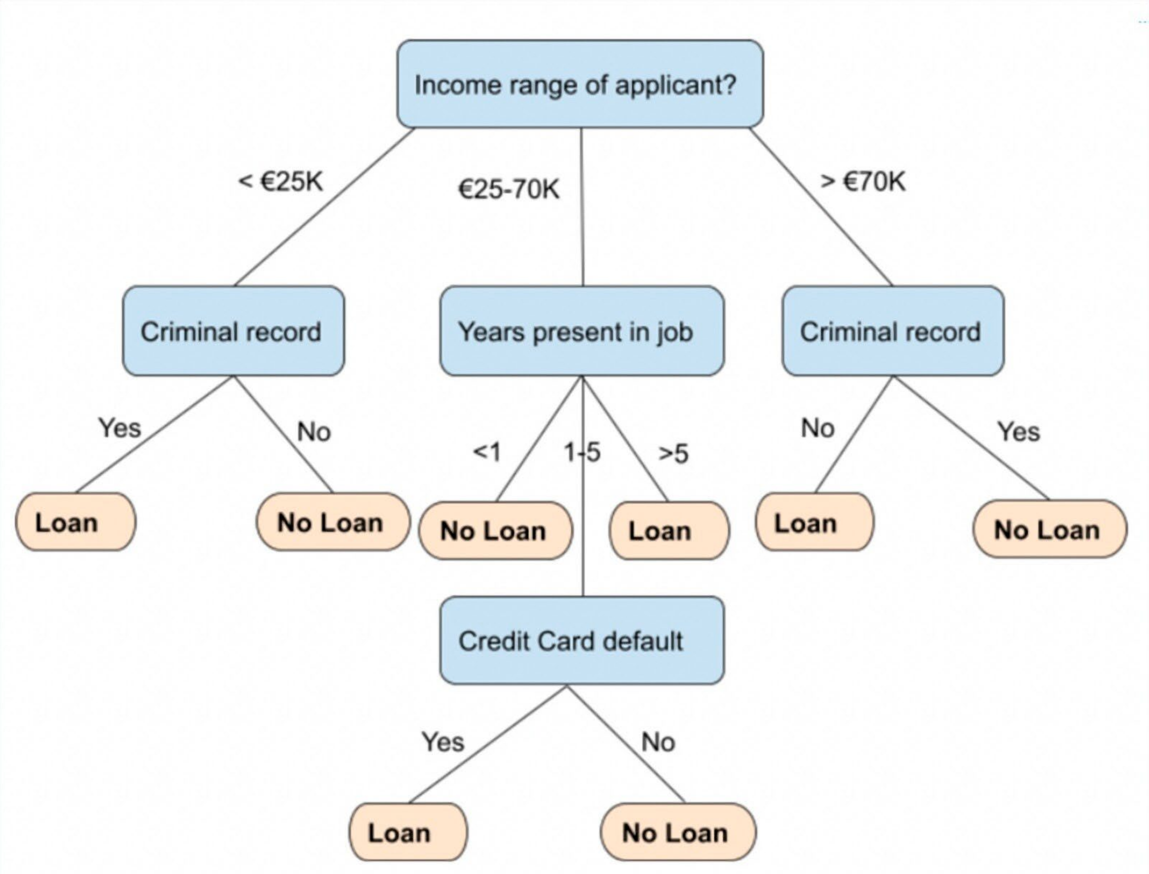
link the input values to a hidden layer, and the hidden layer to the output values. ANNs can easily handle non-linear and interactive effects of explanatory variables due to the presence of many hidden layers and neurons.

Decision trees and random forest

In a decision tree, an input is entered at the top; as it traverses down the tree, the data are bucketed into ever smaller subsets. A decision tree builds regression or classification models in the form of a tree structure. It breaks down a dataset into smaller and smaller subsets while at the same time an associated decision tree is developed incrementally. The final result is a tree with decision nodes and leaf nodes. In the hypothetical example shown in Figure 4, the tree determines whether to provide a loan to an individual based on four variables: income range of the person, years present in the job, credit card default status, and existence of a criminal record.

A decision tree is the most basic unit of the random forest. Random forests combine decision tree predictors, such that each tree depends on the values of a random observation list sampled independently, and with the same distribution. Thus, the random forest approach combines the predictions of many trees, and the final decision is based on the average of the outputs of the underlying independent decision trees.

Figure 4 Decision tree for loan procurement



3.2 Unsupervised Learning Techniques

K-means clustering

The objective of K-means clustering is to cluster the unlabeled data set into K clusters (groups), where data points belonging to the same cluster must have some similarities. As such, the distance between data points is the measure of similarity. Therefore, K-means clustering seeks to find a set of K cluster centers, such that the distances between data points and their nearest center are minimized (Coates & Ng, 2012).

An example of a simplified algorithm:

1) Clusters the data into K groups, where K is predefined.
2) Select K data points at random as cluster centers.
3) Assign objects to their closest cluster center according to the Euclidean distance function.
4) Calculate the centroid or mean of all objects in each cluster.
5) Repeat steps 2, 3, and 4 until the same points are assigned to each cluster in consecutive rounds.

In practice, K-means is a very fast and highly scalable algorithm. Moreover, there is an online stochastic version of K-means (Jumutc et al., 2015) that enables it to scale to big data application. However, this approach also has limitations because it uses the Euclidean distance as measure of similarity. This restricts the types of data variables that can be considered, and cluster centers are not robust against outliers. Additionally, the K-means algorithm assigns each data point to only one of the clusters, which may lead to inappropriate clusters in some cases (Likas et al., 2003).

For proper data science and analysis, it is necessary to determine which task should be accomplished out of the various possibilities, ranging from understanding the internal structure of the data to finding unusual data points and to prediction of values and categories. The current body of literature focuses on prediction tasks, which leaves room to conduct the other types of tasks mentioned. Here we have limited the scope of our review to supervised and unsupervised learning techniques, highlighting the techniques applied most widely in the pensions industry.

To discover the structure of unlabeled data, clustering algorithms can provide the most appropriate tools. K-means clustering, described above, is the best known and most frequently applied clustering algorithm. It can handle large data volumes with a broad range of data types.

The linear regression, random forest, and SVM methods described above are the three most frequently applied algorithms to predict values and classify sequenced data. The objective of the models applied in these algorithms is to process and train data at high velocity.

The most accessible and interpretable way for predicting the categories of data is logistic regression. Neural networks are also suitable learning models for function approximation problems. Moreover, because the volume of pension data is often huge and varied, it requires extensive training; an appropriate solution for this is a multi-class neural network. SVM is another popular classification algorithm, which is capable of handling massive amounts of data and classifying their different types. Because SVM can handle a high volume and a variety of data types, it is commonly applied in data processing algorithms. Caruana & Niculescu-Mizil (2006) provide comparisons of the data science techniques covered in this review.

4. Data Science in Pensions

One way of applying data science in portfolio management is to conduct detailed market simulations. By analyzing swathes of data, algorithms can exploit hundreds of investing patterns all at once, predict investor behavior, and help provide more targeted results for the client. The rise of big data means that fund managers have access to more information than ever before when making decisions for their clients. Applying ML models to analyze the data opens up new opportunities and, as a result, enhances the investment process.

Table 1 provides an overview, based on the papers reviewed, of the machine learning algorithms used for pension data analysis, the cases where it was applied, the type of machine learning tasks, and references where the respective techniques were applied.

We identified three areas where machine learning can lead to better decision making in the pensions industry:

1) Customer-focused approach
2) Organizational process optimization
3) Personnel optimization

Customer-focused approach

Here the focus is on the customers of the pensions industry, in particular retirees. For example, Salazar & Boado-Penas (2019) employed machine learning techniques (logistic regression, SVM, and random forest) to predict early retirement, using data from private pension plans in Mexico. Social and macroeconomic variables were used as predictors for whether an individual retires before the age of 65.

The *Finnish Centre for Pensions* announced that it had taught a machine-learning algorithm to predict retirement on a disability pension, based on socioeconomic, earnings, and benefits data. It achieved a 78% accuracy rate of detecting who is likely to retire on a disability pension[3]. *Mercer Global Australian Business* recently launched the Mercer 'Superbot', which is a financial advice chatbot accessed through Facebook Messenger[4].

Leung et al. (2019) used tweets from *StockTwits* and sentiment analysis from natural language processing (NLP), which is akin to logistic regression to predict stock

3 https://www.actuview.com/predicting-disability-pensions-with-machine-learning-classification-models_cb510e136.html

4 https://www.mercer.com.au/our-thinking/superannuation/meet-superbot-artificial-intelligence-delivering-financial-advice.html

Table 1. Overview of machine learning algorithms for pension data analysis (based on the papers reviewed).

Machine learning technique	Cases	Data processing tasks	Representative references
Logistic regression	Retirement prediction	classification	Salazar & Boado-Penas (2019), Bosworth & Burtless (2010) , Coile & Levine (2011), Blekesaune & Skirbekk (2012), Feldman & Beehr (2011)
Sentiment analysis	Stock return prediction	classification	Leung et al. (2019)
K-means clustering	Pension scheme selection	classification/ recommendation	Dong et al. (2017), Cong et. al (2016), Gough & Sozou (2005)
SVM	Retirement prediction, asset management	classification/ regression	Salazar & Boado-Penas (2019)
Decision tree	Pension fund asset valuation	classification	Aguirre et al. (2019)
Random forest	Portfolio management, asset management	classification/ regression	Salazar & Boado-Penas (2019)
Lasso regression	Defined benefit obligation	regression	Hendriksen (2017), Rapach et al. (2018)
Reinforcement learning	Portfolio management	classification	Cong et al. (2020) Snow (2019)
ANN	pension cost dependency ratio, stock returns prediction, asset management, emotion recognition	classification/ regression	Agnieszka (2018), Avramov et al. (2019), Henkel et al. (2020)

return trends. They found that social-media sentiment positively and significantly predicts future stock returns, and, importantly, that such positive predictability decreases when the number of stocks that users follow increases.

Dong et al. (2017) and Cong et. al (2016) developed a recommendation system from customer attribute information including age and gender. Together with a user interest model based on online interfaces provided by pension service providers such as click-through rate, they developed a recommendation system of pension services to similar users.

Gough & Sozou (2005) studied the variation in behavior and attitudes such as debt tendency with regards to pensions and retirement saving among consumers of financial service products. Using data obtained via a questionnaire, they carried out K-means clustering analysis as the methodology for their study.

Various other studies have been conducted to determine the explanatory factors of retirement decisions. Some studies find that macroeconomic factors such as unemployment rate and stock market performance affect the decision of people to enter retirement early or to delay it (Bosworth & Burtless 2010, Coile & Levine 2011).

Other studies show that personality traits can predict the timing and routes of a person's retirement (Blekesaune & Skirbekk 2012, Feldman & Beehr 2011). In the context of a private company such as an insurance company that offers retirement plans, the retirement decisions are of interest because an early retirement involves fewer contributions to the system, less investment, and therefore lower net earnings. More generally, companies need to predict when and how much of the budgetary provision will be needed to make payments when pensions are claimed.

Organizational process optimization

The goal of process optimization is to significantly improve the core operations of the pension provider such as portfolio management, asset management, and stock forecasting. Snow (2019) highlights various machine learning techniques for portfolio optimization, risk management, and capital management[5]. This author also provides numerous examples that touch on most of the aforementioned machine learning techniques and their financial application, as follows:

Werpachowska (2018) analyzed and forecasted the pension cost dependency ratio for England and Wales from 1991 to 2061, in a bid to evaluate the impact of current state pension reforms and changes in international migration patterns under different Brexit scenarios. She analyzed mortality rate model based on deep learning techniques to account for the volatility in life expectancy, to discover complex patterns in the data as well, and to extrapolate trends. The results show that the recent reforms can effectively stave off the "pension crisis" and bring the system back on sounder fiscal footing.

Aguirre et al. (2019) developed a model that allows one to predict the pension fund of an affiliate in the private pension system by means of a web solution. A boosted decision tree which is similar to the random forest was used to create the model and evaluated using the Pension Fund Administrator (AFP) in Lima (Peru).

Hendriksen (2017) investigated the feasibility of predicting defined benefit obligation (DBO) using a statistical/machine learning approach with some success regarding accuracy of prediction. Salary, age, gender, and the ratio of back service to total service time were explored as explanatory variables, using a Generalized Linear Model.

Otranto & Trudda (2008) used an agglomerative clustering algorithm, based on the distance between time series model of the volatility for different pension funds, applying GARCH models. This provided a classification of the funds based on different

5 This paper provides various examples, which can be found at: *https://ssrn.com/abstract=3420952*

degrees of risk, since similar GARCH models represent similar volatility behavior and similar investment risks.

Avramov et al. (2019) examined empirical evidence of the economic importance and statistical reliability of ANN to predict cross-sectional stock returns and asset management.

Rapach et al. (2018) used lasso regressions to analyze industry return predictability based on the information in lagged industry returns. Controlling for post-selection inference and multiple testing, they found significant in-sample evidence of industry return predictability.

Cong et al. (2020) developed a reinforcement-learning-based portfolio management to directly optimize investors' objectives. This is an alternative that improves upon the traditional two-step portfolio construction.

In Denmark, *PensionDanmark* has automated around 80% of its administrative decisions and aims to increase this further. In the United Kingdom, the Department for Work and Pensions is using AI to crack down on benefits fraud[6].

This overview shows that the area of business optimization uses a diverse set of data science applications, covering many types of machine learning techniques that range from supervised techniques to reinforcement learning.

Personnel optimization

Sasaki et al. (2018) studied the feasibility of using AI for fund manager structure development at the behest of the Japanese Government Pension Investment Fund (GPIF). A joint team, consisting of GPIF and Sony representatives, examined the management structure development and maintenance processes of GPIF. They explored the use of a proof-of-concept prototype system to test the principle of applying ANNs to detect the investment style of managers, based on trading behavior data (trading items, timing, volume, unrealized gain and loss, etc.) collected on a daily basis by GPIF.

Essentially, research that focuses on augmenting the personnel workspace in a pension organization falls in the personnel optimization category. Another example is Henkel et al. (2020), who developed AI-based emotion recognition software that helps service employees in managing customer emotions while interacting with them. The case scenario of focus was two pension funds in the Netherlands that provided access to their centralized call center operations.

6 https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/721224/dwp-annual-report-and-accounts-2017-2018.pdf

5. Discussion

In order to exploit the full potential of data science, we identify three major challenges for the pension industry, which are described below. In addition, we briefly discuss the similarities and differences between econometrics models and machine learning models.

Data collection and quality

Because data are the basis of the extraction of knowledge, it is vital that these are of high quality to ensure robust predictions and sound analysis. Most countries have put in place strong policies for pension agencies to collect and provide relevant data to ensure transparency. As a result, the pension industry produces a high volume of data at high speed and in different varieties. Each of these (volume, speed, variety) separately makes preservation of data quality a challenging task, and considered together they make the preservation of quality a daunting endeavor. The ways that data are collected and stored are often not suitable to directly apply data science techniques on them. Data integration is another major issue, since different departments or agencies in the pension industry mostly generate raw data that are often not suitable for straightforward analysis. Different solutions have been proposed two tackle these problems, but many of these solutions require further refinement. For instance, semantic technologies such as knowledge graphs and ontologies can be used to structure data better and to provide semantics, while facilitating data sharing and integration. Other solutions include methods for designing data management systems with data ready for machine learning as output.

Privacy and security

Privacy and security issues should be considered when running data analysis in pension applications. First, the privacy of collected data is highly critical, because personal or critical business data can be involved. Second, the various data providing agencies often apply different data security policiess, so it is vital to consider how the various policies within a single data science system can be aligned.

Interpretability vs accuracy

Considering the characteristics of pension data, analytic algorithms should be able to handle large volumes. In other words, the pension industry requires algorithms that can analyze data that come from a variety of sources in real time. Many attempts have been made to address this issue. For example, deep learning algorithms, which are a form of neural networks, can be applied through online training to cope with real time application. Studies show that they can reach a high accuracy rate, provided that the data are sufficiently rich and that there is time for training. However, deep learning algorithms are sensitive to noisy data. Another issue is that neural network-based algorithms lack interpretation, that is, data scientists often cannot unambiguously interpret the model results.

6. Conclusion

Given that artificial intelligence and data science are relatively young fields, their application in the pension industry is still in an early phase. So there is much potential to adopt state-of-the-art methodologies for solving challenges in the pension industry. This article surveys the existing body of academic literature to summarize how data science is being currently leveraged to deal with issues related to pensions. The focus of most studies discussed here is on prediction tasks and chatbot development. There remains ample room for more unsupervised learning like clustering that uses the latest methodologies, NLP techniques to glean insight from text and social media data, and applications of reinforcement learning.

Our survey identifies three streams of applications of data science in the pensions context: a customer-focused approach, organizational process optimization, and personnel optimization. Customer-focused approaches are mostly applied to research on retirees or potential retirees, ranging from prediction of individual preferences to services provided. Organizational process optimization and personnel optimization focus on the pension providing agencies themselves and their workforce.

There is a vast amount of data that is hardly ever used. Data science can use these idle data and has the potential to, for example, detect societal groups with insufficient pension savings. Also, data science could be used to detect and aid customers who face diversification decisions regarding their savings.

There are still a number of challenges that need to be overcome for an effective application of data science in the pensions framework. Data collection and quality need to be standardized to enable straightforward integration into the data science workflow. Security and privacy protocols need to be properly laid out and addressed. Research into science techniques to enable the interpretability of blackbox data is a worthwhile area for future research.

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