Machine Learning in Automated Asset Management Processes 4.1

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Summary: The traditional (human driven) process of Asset Management has become automatized by algorithmic decision trading with so called Robo Advisors (RAs). With an increasing amount of publicly available financial data, the foundation for applying machine learning (ML) algorithms has been paved. We examine the question in which process steps of automated investment advice ML algorithms could be applied and investigate which implementations have already been placed on the market. As the following study shows, (surprisingly) ML is globally still under its development phase in Robo Advisory. German and Swiss FinTech companies thereby contribute about a third to the ML solutions in our sample. The most promising technique is the usage of Text Mining for sentiment analyses, which can be used for monitoring and rebalancing purposes or future performance forecasting. Furthermore, Text Mining algorithms can be helpful for reducing information asymmetries. Embedded into early warning systems, the derived sentiment scores can be used for hedging against future price losses. This approach would be inevitably linked to an increased access of highly sensible data. Furthermore, we try to provide an explanation for the lack of acceptance of the application of ML in RA distributions. Possible reasons for this can be found in the current MiFID II regulations, which are not specified for ML. Based on these insights, we formulate first recommendations for both the provider of RA solutions as well as for the regulator.

Keywords: Diversification, decision-making processes, financial and security analysis, information management, artificial intelligence and business administration, optimization methods, portfolio theory, risk management

Maschinelles Lernen in automatisierten Vermögensverwaltungs-Prozessen 4.1

Zusammenfassung: Der traditionelle (eher menschlich geprägte) Prozess der Vermögensverwaltung wird immer weiter durch algorithmisch getriebene Entscheidungsprozesse automatisiert. Diese können entweder vollständig automatisiert sein, so genannte „Robo Advisor“ (RA), oder teilweise automatisiert, als hybrider Ansatz zum traditionellen Anlageprozess. Mit einer ansteigenden Menge verfügbarer Finanzdaten wurde die Grundlage für die Anwendung von Machine Learning (ML) im Bereich Robo Advisory gelegt. Wir gehen

der Frage nach in welchen einzelnen Prozessschritten der automatisierten Anlageberatung ML-Algorithmen Anwendung finden können und analysieren, welche Implementierungen bereits am Markt platziert wurden. Wie die zugrundeliegende Studie zeigt, befindet sich die Anwendung von ML global (überraschenderweise) noch in der Entwicklungsphase. Deutsche und schweizerische FinTechs nehmen dabei knapp ein Drittel der ML Lösungen in unserer Stichprobe ein. Eine vielversprechende Technik stellt die Anwendung von Text Mining Algorithmen in *Sentiment*-Analysen dar, die zu *Monitoring*- und *Rebalancing*-Zwecken oder zur Vorhersage zukünftiger Renditen eingesetzt werden können. Darüber hinaus können Text Mining Algorithmen zum Abbau von Informationsasymmetrien genutzt werden. Eingebettet in Frühwarnsystemen können die abgeleiteten *Sentiment Scores* zur Absicherung künftiger Preisverluste eingesetzt werden. Dieser Ansatz wäre unweigerlich mit einem verstärkten Zugriff auf hochsensible Daten verbunden. Darüber hinaus versuchen wir einen Erklärungsansatz für die mangelnde Akzeptanz der Anwendung von ML in RA-Distributionen zu liefern. Mögliche Gründe hierfür finden sich in den nicht für ML spezifizierten MiFID II Regularien. Daraus formulieren wir erste Handlungsempfehlungen sowohl für den Anbieter von RA-Lösungen als auch für den Regulator.

Stichwörter: Diversifikation, Entscheidungsprozesse, Finanz- und Wertpapieranalyse, Informationsmanagement, Künstliche Intelligenz und Betriebswirtschaftslehre, Optimierungsverfahren, Portefeuille-Theorie, Risk Management

JEL Classifications: C61, D46, D81, E37, G11, G17, O31

1. Machine Learning in Asset Management 4.1

1.1 Market Overview and Research Outline

The trend towards digitalization has just recently encountered one of the most traditional topics in finance – the study of wealth investments (*Beketov et al.* 2018). The traditional, more human driven, process of Asset Management has become more and more automatized by algorithmic decision trading. Due to an increasing amount of available financial data, the foundation for applying Machine Learning Algorithm (MLA) has been paved. With the rise of fully automated investment machines, also known as Robo Advisors (RAs), a less costly alternative for retail investors has arisen in contrast to the traditional, more costly wealth management process. Another emerging trend is to use algorithms as a supporting tool in the traditional Asset Management to reduce costs and optimize sales materials and reaction times to clients.

The Statista Digital Market Outlook forecasts that the total assets under management (AUM) by RAs globally, will increase from USD 987.5 billion in 2020 to as much as USD 2.5 trillion by 2024 (*Statista* 2020). Obviously, the ongoing COVID-19 pandemic along with more general factors, such as a general trend for digitalization, a new generation of investors, and increasing quality of the RAs around the world, will be important factors driving the AUM up over the next few years.

In the current dataset there were only about USD 80 billion of AUM by funds being associated with MLA whereas only USD 20 billion of these funds consisted of pure RA solutions. In the following we would like to address three major questions covering the incorporation of MLA within RA:

1. What are possible use cases of MLA in automated investment advice?
2. How are these possible applications already being established in practice?
3. What are the limitations for the incorporation of MLA in RA?

In section 1 we briefly introduce the basic five standard tasks in automated investment advice that are potentially exposed to the application of MLA, i.e. *Asset universe selection, Investor profile identification, Asset Allocation, Monitoring and Reporting*. Some use cases also consisting of our daily business analysis, like *K-Nearest Neighbor (KNN)* classification in investor profile identification, *Long-Short-Term-Memory* (*LSTM) and Hidden Markov Models (HMM)* in stock price regression and forecasting analysis are then presented. In section 2 a quantitative and qualitative analysis to further investigate the current use of MLA already in store and highlight limitations of the research design are conducted. As our research shows, (surprisingly) the application of MLA in Asset Management is still at its development phase. A possible reason for this can be found in the missing regulatory framework for using MLA according to the current MiFID II regulation. Section 3 summarizes the paper, points out the synergy effects between Text Mining and RA, and gives additional recommendations for the Robo supplier as well as for the Robo regulator.

1.2 General Framework of Automated Quantitative Asset Management 4.0

Following the Modern Portfolio Theory (MPT) by *Markowitz* (1952) and *Markowitz* (1959) as well as the traditional capital asset pricing model (CAPM) designed by *Sharpe* (1964), *Lintner* (1965) and *Mossin* (1966), the investor's ultimate goal is to maximize future expected returns at a given level of risk.[1] While the more risk adverse investor is more likely to invest in mutual risk-free bonds, like federal state bonds or AAA rated corporate bonds, the risk seeking investor wishes to invest in equity funds or speculative bonds with a credit rating of B onwards (following the investment grade of Moody's). However, as the efficient market hypothesis by *Fama* (1970) states, without insider knowledge it is most unlikely for a 'normal' retail investor to beat the average performance of the market portfolio (e.g. the MSCI index). With this theoretical background in mind, the traditional (mostly driven by humans) task of Asset Management has shifted the focus into finding the most cost-efficient portfolio. More modern alternatives to the outdated MPT are Risk Parity (*Rocalli* 2013) and Full-Scale Optimization (*Cremers et al.* 2005, *Adler/Kritzman* 2007). For Risk Parity, each risky asset contributes a constant amount of risk to the overall portfolio volatility. Full-Scale Optimization is taking the investor-specific utility function as objective also accounting for the risk of a two- or even three-sigma loss.

Three groundbreaking transformations in finance formed the basis for cost-efficient automated quantitative Asset Management. First, the ability to invest in exchange traded funds (ETFs) which are passively managed investment vehicles. The first ETFs were inserted in the early 1990s in Canada (TIPs) and the U.S. (SPDR). The idea to trade a whole portfolio in a single transaction dates back to 1970, when U.S. brokerage firms allocated program trading facilities notably for the S&P500 index (*Deville* 2008). Today's ETFs replicate an underlying stock index (like MSCI, S&P500 or DAX) by minimizing a tracking error that describes the difference between the underlying index and a portfo-

1 Equivalently it can be said that an investor tries to minimize risks (based on a specific risk measure) for a desired or given rate of return.

lio, consisting of either physical stocks (of the same index) or derivatives. Secondly, the amount of ever-growing financial data (Big Data) form the basis for input data. Thirdly, increasing computing power as well as increasing storing capacity, provides the methodological feasibility for building a Robo Advisor.

ETFs, Big Data and improving technology make it possible for Robo Advisors to invest massive amounts of AUM. Beside this, RA solutions benefit from an emerging acceptance towards digitalizing financial services.

The traditional tasks of Asset Management can be subdivided into five categories (following *Beketov et al.* 2018).

I. *Asset universe selection:* Traditionally asset managers choose stocks or other assets based on their personal choice of investment figures, like earnings per price (E/P), earnings per share (EPS), dividend yield (DY) or book-to-market value (BMV). Other asset managers choose qualitative performance measures for portfolio selection purposes, like brand awareness, newspaper articles or publicly available investment brochures. Most RAs pre-dominantly focus on quantitative investment figures. However, there are applications, like the approach of *Black/Littermann* (1992) adding publicly available information and expert meanings to the scope of investment decisions.

II. *Investor profile identification:* These are most likely questionnaires regarding the investor's current financial status determining the traditional investor type divided in, for example, one of three categories: the risk-averse investor predominantly investing in bonds, a risk-neutral investor investing in bonds and stocks, and a risk-seeking investor predominantly investing in stocks. Subcategories of the investment horizons are possible and used in the market by e.g. more active RAs who construct individual portfolios for each client instead of mapping the categories to pre-optimized representative portfolios.

III. *Asset allocation or portfolio optimization:* As the MPT states, the typical investment decision breaks down into a convex minimization problem incorporating measures of performance, like expectation of returns, risk (volatility) or higher moments (like skewness and kurtosis).[2] Sometimes an analytical solution to the above mentioned optimization problem can be found by solving the Lagrangian dual problem. If this is not the case, a solution is approximated by a numerical solution with the use of Monte Carlo simulation for example.

IV. *Monitoring and rebalancing:* As the status of economy changes, the amount of newly gained and publicly available information grows exponentially. Conclusively the investor's portfolio choice has to be updated in order to meet the altered environment. Since rebalancing of the portfolio is inevitably linked to transaction costs, the asset manager has to find a well-balanced time horizon when to update the client's portfolio weights. Daily rebalancing would suppress the daily performance and, in the worst case, would even result into portfolio losses. Yearly rebalancing would miss out important events that occurred in the market, like under-year statements, financial crises or important political election results. Therefore, RAs typically ad-

2 The idea of diversification and portfolio optimization originally states back to the work of *Markowitz* 1952.

just the portfolio amounts when a threshold is hit or periodically like once a month or once a quarter.

V. *Performance review and reporting:* Performance review is important since it permanently validates the actual investment model and highlights discrepancies between past investment choices and realized performance figures today. Dashboards help to overview future possible exposures and possible losses after each round of rebalancing. Some investors might have lower bounds of capital budgets that force the optimization algorithm to deny certain levels of risks. Typical risk measures are value at risk (VaR), conditional value at risk (CVaR) or mean Variance (MVaR). A numerical way to evaluate risk exposures can be given by using Monte Carlo simulations. With these reporting mechanisms, the RA also backups its portfolio choice from a regulatory perspective by fulfilling current MiFID II regulations (introduced in January 2018 in the EU).

As will be shown, each of the above five categories (labelled I-V in the following) is suitable to the application of machine learning algorithms.

1.3 Methods of Machine Learning-Algorithms suitable to Automated Asset Management 4.1

Machine Learning (ML) describes a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty (*Murphy* 2012). A more formal definition of ML traces back to *Mitchell* 1997:

> "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E."

More simply formulated: The ability of an algorithm to learn certain tasks is based on the fact that experiences are trained and thus can be used to perform actions in a new (unseen) environment. As a result, software developers no longer have to follow deterministic coding principles in order to solve the underlying tasks I-V as described in the previous section. In the following, we would like to present some use cases about how to apply ML in standard RA tasks.

Classifying (Category I-II)

Machine Learning Algorithms became prominent with image and speech recognition applications, for example, k-nearest neighbors (KNN) (*Murphy* 2012). For Asset Management purposes, an obvious classifying problem would be to cluster different asset types from the underlying asset universe (category I). For instance, different ETFs from the portfolio selection could be chosen and classified according to fixed-income, equity or commodities, based on features like Sharpe-Ratio (SR) and last years' return (LYR) as presented in *figure 1*. KNN now searches for the k-nearest neighbors[3] with similar SR and LYR. The algorithm chooses the majority of classes around the to-be-classified asset, i.e.

3 A measure of "nearest" could be the Euclidean distance for example. Other norms are possible like the absolute value norm or the maximum value norm.

with k = 3 a majority would be two neighbors of one and the same asset class.[4] Another application would be to classify assets suitable to different investor profiles (category II).

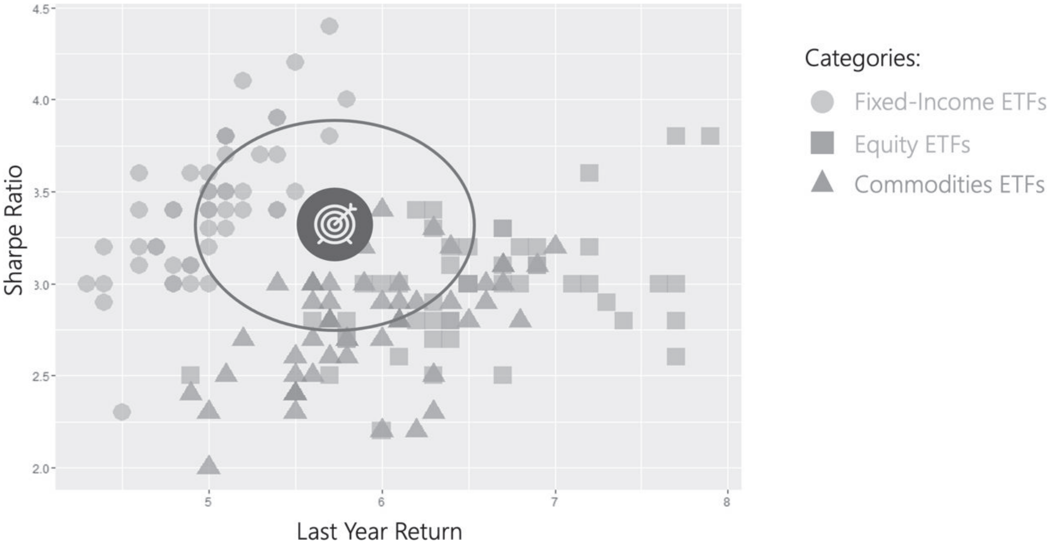

Figure 1: ETF universe selection based on a KNN-algorithm with two input features: Sharpe ratio (in %) and last year return (in %)

Source: Deloitte internal analysis 2019

Optimization (Category III)

Ban et al. (2016) give a practical example for the use of ML in portfolio optimization by applying regularization and k-fold cross-validation techniques to minimize risk measures such as MVaR and CVaR. The presented algorithm dominates two out of three Fama-French models.

Forecasting/Regression (Category IV to Category V)

One of the most desirable features in risk management is the attempt to predict future performance measures of the underlying risky portfolio assets such as return and volatility. Traditional approaches like the MPT and CAPM are based on estimates from the past. Although, the Arbitrage Pricing model by *Ross* (1976) clearly formulates that future returns rely on future expected discounted cash flows, currently established augmentations like the *Fama/French* (1993) three-factor model and the *Carhart* (1997) four-factor model still base on the assumption that future returns rely on historic time series. The ARCH and GARCH models described by *Engle* (1982) and *Bollerslev* (1986) respectively, try to resolve the-non-stationarity of performance measures, especially regarding volatility. Still, pitfalls like market inefficiency, measurement errors or inappropriate statistical inferences arise (*Jorion* 1995). Further, non-rationalities of investors lead to failure of traditional market models (see *De Bondt/Thaler* (1995), *Daniel et al.* (1998) as well as *Odean* (1998) for documented examples). Attempts to unify established models like GARCH with recent

4 Usually an uneven number of k is chosen, in order to find a unique decision for the predicted cluster.

ML developments like Long Short Term Memories (LSTMs) for example, are presented in *Kim* (2018). LSTMs originate from works of *Schmidhuber/Hochreiter* (1997) and belong to the subgroup of Recurrent Neural Networks (RNN) that remember previous state information (tracing back to 1000 steps). Beside the traditional input gate (for training data) and the output gate (for predictions), LSTMs offer an additional Forget Gate that separates relevant from irrelevant information by matching new experiences to already stored experiences. Further, LSTMs overcome the problem of vanishing and exploding gradients that image the learning rate during the calibration process.[5] In *figure 2* a 5-Layer LSTM regression on daily DAX Performance index data was preformed over a 7-year cycle, starting from January 2008 to December 2015 (gray line). The first 67 % of the data was used to train the model on 20 epochs with batch size 5 (dashed line). The remaining 33 % of data was used to perform a one-day-ahead daily stock forecast of the underlying index (dotted line). The rooted mean square error (RMSE) was about 1.07 for the training data and 2.59 for the test data.

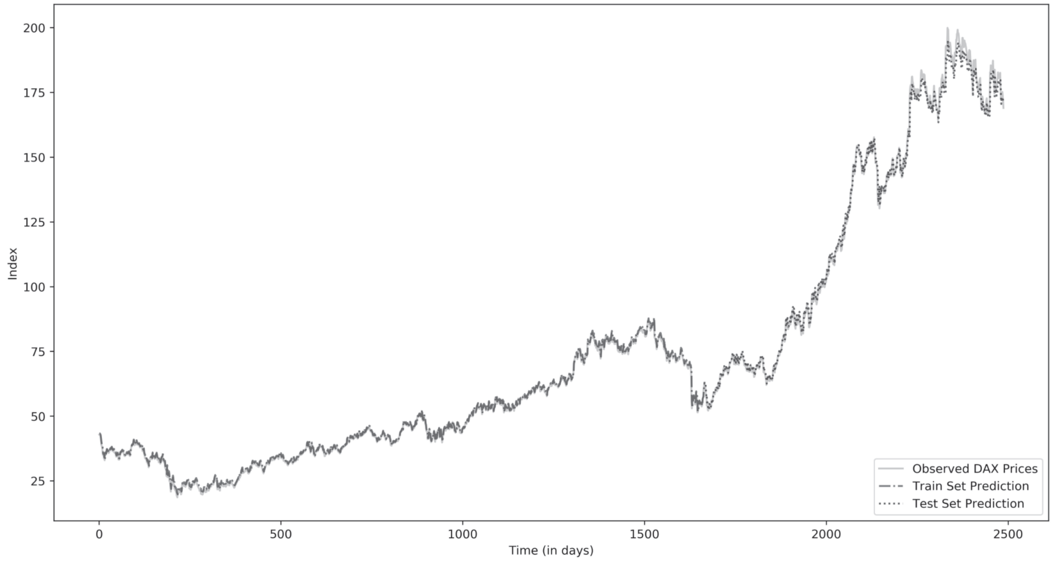

Figure 2: LSTM-Stock forecasting as of the example of 7y DAX Performance Index (grey line). The first 67 % of the data were used to train the 5-Layer-LSTM-Network (dashed line). The remaining 33 % test data were used to make one-day-ahead forecasts (dotted line).

Source: Deloitte internal analysis 2020

Another ML solution indicating up- and downtrend phases in the underlying stock market is the Hidden Markov Model (HMM) as described in *Rabiner* (1989). *Figure 3* shows two time series of the S&P 500 index. Above, 200 data points of daily stock prices were mapped. Below, we mapped the same data points to the S&P 500 daily returns. A straight line on top indicates a downtrend phase, whereas a straight line on the bottom corresponds to an uptrend phase. One special feature about HMMs is that it introduces a

5 For an overview of gradient-descent procedures, please refer to *Pearlmutter* (1995).

new two-phase process (up- or downtrend phases) given an estimated density distribution of the underlying price/return index, which is assumed to be a Markov chain process.

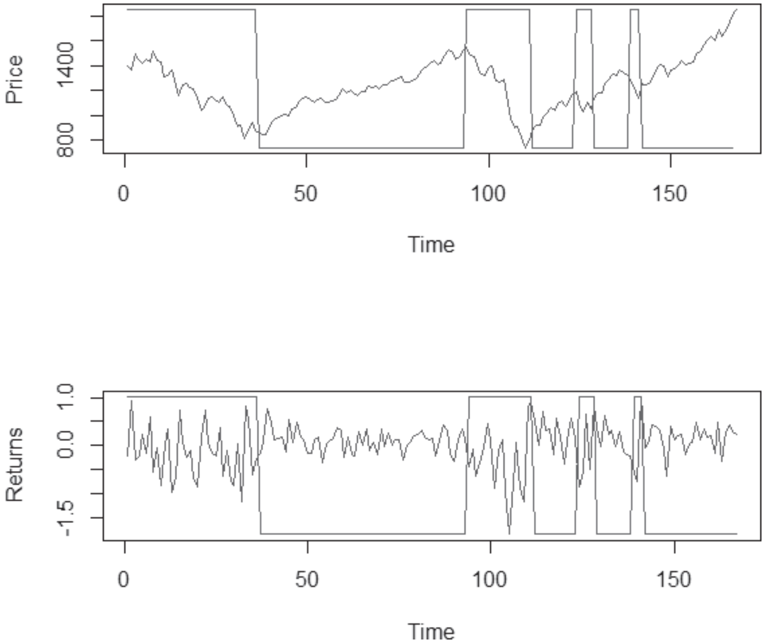

Figure 3: Up- and downtrend phases using Hidden Markov Chains at the example of S&P 500 price versus time data (above) and returns versus time data (below).

Source: Deloitte internal analysis 2019

Text Mining (Category II and IV to V)

Text Mining uses high amounts of unstructured text data as input and produces structured output data via MLA. Text Mining can be used to evaluate product information, newspaper articles or news feeds that have the potential to affect future returns of the underlying investor's portfolio. An additional application would be to use social media data as additional input parameter for determining buy and sell orders. Recent studies like *Tetlock (*2007), *Das et al.* (2007), *Luo et al.* (2013) and *Bartov et al.* (2018) have already discovered statistical evidence that sentiments have a significant impact on stock market returns. The value of public opinion therefore is a non-negligible factor explaining future performance and thus should be incorporated into future forecasting models in RA solutions (categories IV-V as of section 1.2).

Further, Text Mining can be used to support all kind of classification tasks as described in category II of the previous section. If linked to the personal online banking account, Text Mining automatically collects factors indicating the investor's risk tolerance level, such as age, income, financial goals or saving plans. This process is inevitably linked to an increased access of highly sensible data that must be treated in line with the current regulatory framework such as MIFID II.

2 Empirical Analysis of Machine Learning Algorithms used in Robo Advisory

2.1 Research design and database

The present analyses are based on a set of systems that could be considered as RAs or RA affiliated FinTechs, both in B2C as well as in B2B markets. This list was compiled during extensive research performed previously by the authors as already described in *Beketov et al.* (2018 unpublished database). The data set included the RAs from 28 countries, with 30 % of the companies located in USA, 20 % in Germany, 14 % in UK, 9 % in Switzerland, and the rest 27 % in other countries. The RAs in the data set were founded from 1997 until 2017, with the average founding year 2014 (the most frequent years are: 2016 – 48 %, 2015 – 16 %, 2017 – 15 %, and 2014 – 14 %). The AuM volumes of the analyzed RAs ranged from USD 1 million to 93 billion with the average and median values being USD 3.7 billion and 0.9, respectively.

In this new approach, we analyzed the web pages of these systems and performed a site search consisting out of the following buzzwords: "Machine Learning", "Artificial Intelligence", "ML", and "AI". Questionnaires were not actively sent out to the companies. Furthermore, qualitative research was carried out by browsing through the systems' web pages in more detail and collecting information that refer to the incorporation of Artificial Intelligence (AI). The buzzwords were collected in a summary table and were independently four-eye reviewed by a research colleague. *Table 1* in the appendix shows an anonymized sample of this selection process.

By adding another content analysis, we observed that the AUM for funds associated with automated investment advice did not exceed USD 80 billion. However, only USD 20 billion of the latter referred to pure, i.e. in the narrow sense complete, Robo solutions. These numbers have to be treated with caution since they are subject to the following constraints:

- As for most RA's, information on AUM figures is usually not publicly available. AUM information is therefore partly collected from third-party business newsfeeds.
- The differentiation between ML and Non-ML driven (but still quantitative oriented) funds is hard to maintain.
- Some FinTech companies (mainly in the B2B sector) only distribute sub-integrated ML solutions that cannot be directly linked to AUM of their client firms.

All the software solutions we found are based on machine learning algorithms (MLA), which is a sub-category of AI solutions. In addition, Artificial Neural Networks (ANNs) and Deep Learning (DL) as conglomerate of ANNs belong to this form of sub-category of weak (or narrow) AI. Currently, there is no strong form of AI solutions. A strong (or general) AI would pass the Turing Test and would be able to mimic human-like consciousness and empathy (*Turing* 1950, *Searle* 1980 and *Penchanin/Goertzel* 2007). Furthermore, a strong AI would be able to extend its own programming code (*Omohundro* 2017). Weak AI no longer attempts to imitate the human thought processes and creativity, but rather develops algorithms to solve clearly defined problems (*Goertzel* 2010). This does not mean that a weak form of AI cannot provide a better service in some tasks than a human. For example, in 2011 IBM's Watson, a reinforcement learning algorithm, beat the two former all-time Jeopardy champions Ken Jennings and Brad Rutter (*IBM Research* 2013). Even more recently in 2016, Google's DeepMind algorithm won against the current Go-Champion Lee Sedol, a game that is more complex than chess and cannot be solved by brute-force-algorithms calculation power (*DeepMind* 2016). The algorithm again was based on a combination of reinforcement learning algorithm and Monte Carlo tree search, belonging to the subgroup of DL. Although most current state of the art AI applications are narrow and based on ML, it seems that most software suppliers of RAs prefer using the buzzword AI instead of ML.[6]

In total, only 29 suppliers were offering ML solutions. Among these, there are only four Robo solutions offering ML. However, at second glance, we ascertain that 21 out of the 29 suppliers do not further specify their ML approach. Overall, it yields a total rate of about 21 % of specified ML approaches. A possible explanation for this intransparency might result from the suppliers' fear of losing their competitive advantage. Furthermore, it seems that using the buzzwords AI and ML is a 'must-have' on a FinTech website implying that the offered software solution is not lacking behind digital innovations.

We further analyzed the underlying MLA used by the supplier in more detail. However, as stated above, the theoretical background is often hidden behind the use of marketing buzzwords. To give an example, one Robo investment firm presents its new initiative, which offers a more 'personalized' dashboard using AI. The same picture arises for another website of an EU-based IT developing investment platform which reveals that their MLAs compare bonds, selecting those with predicted 'best' performance. Again, the supplier does not specify the ML application in use. In these cases the underlying MLA approaches were labeled as "not specified" in our study.

We would further like to highlight that our sample of 29 suppliers of affirmed ML solutions consists of a number of globally acting companies from 12 countries, with 34 % of the companies located in USA, 24 % in Germany, 7 % in UK, 7 % in Switzerland, and 28 % in other countries. Due to the small sample size these relative numbers have to be

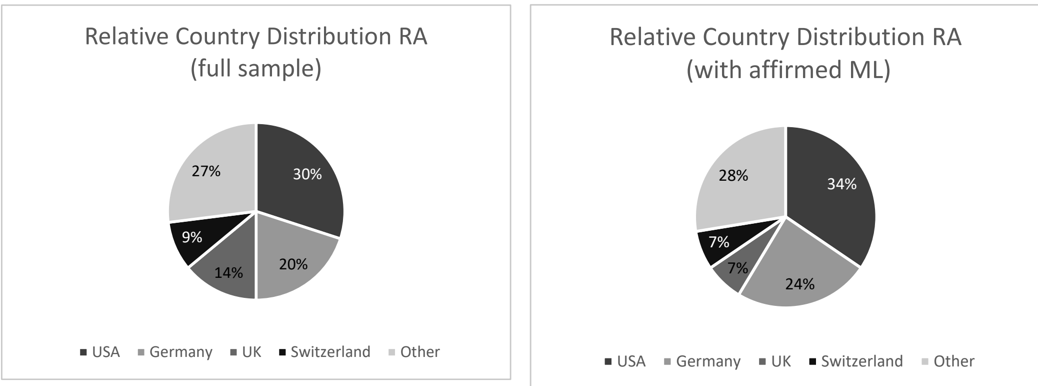

Figure 4: Country distribution among Robo Advisors including ML and Non-ML solutions (full sample left) in comparison with Robo Advisor firms holding ML solutions (right).

Source: Own research 2020

6 From our point of view this might result from the possibility that potential clients associate the wording ML with machines taking over more and more human works. In contrast to this, the AI terminology most likely implies a "brighter" picture of the digital future.

treated with caution but (except for the UK case) the distribution resembles to the full sample distribution of RAs with and without AI solutions (see figure 4). The German and Swiss Market accumulates to 31 % of the global AI solutions.

In absolute numbers, we see that Robo ML innovations only constitute to a small fraction of the overall RA solutions (see figure 5). Seven FinTech solutions offering ML solutions are based with headquarters in Germany and two more FinTechs are based in Switzerland. Another qualitative analysis shows that these nine solutions are – in the narrow sense – no complete RA solutions, i.e. not covering the full asset management allocation process, but rather offer highly specialized sub-ML-solutions that can be embedded in complete RA solutions in the sense of a modular embedding within categories I-V as described in section 1.3. Overall, the results imply that the global RA market is uniformly lacking behind in AI innovations, a fact that contributes to the ongoing debate about enlarging future AI investments.

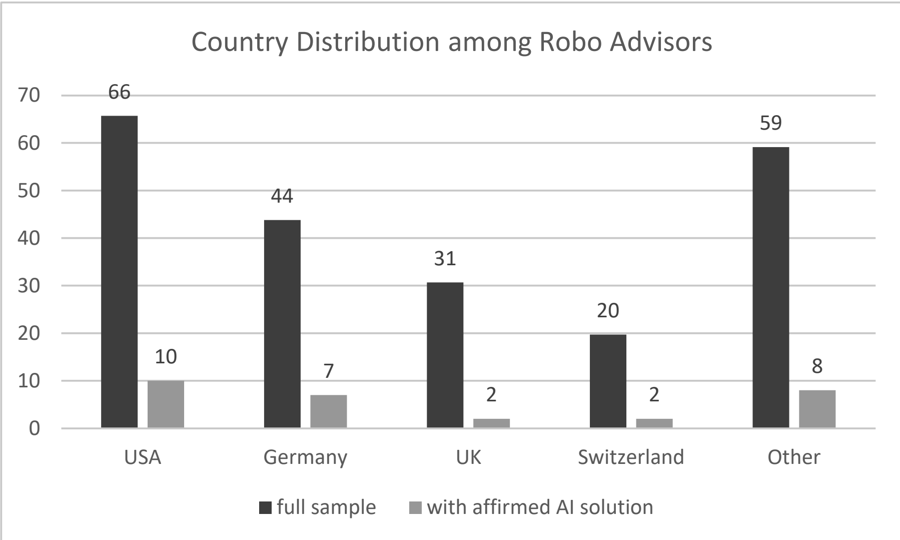

Figure 5: Country distribution of Robo Advisors with affirmed AI solutions (light grey) in comparison to the full sample (dark grey) of Robo Advisors with and without affirmed AI/ML solutions (in absolute numbers).

Source: Own research 2020

Obviously, this technological gap does not remain unrecognized by the European governments. For example, the German *Bundesregierung* plans to invest three billion euros in AI innovations until 2025.[7] In particular, research, education, training on the job and business model innovations will be supported. The derived knowledge will most probably also affect future developments in RA.

7 See „Bundesregierung will drei Milliarden Euro in Künstliche Intelligenz investieren, in: Handelsblatt 13th November 2018, URL: https://www.handelsblatt.com/technik/thespark/digitalklausur-bundesregierung-will-drei-milliarden-euro-in-kuenstliche-intelligenz-investieren/23627702.html?ticket=ST-3181082-0JlesEPSNuNIo30eVaEa-ap2, accessed 28 August 2019.

2.2 Summary Statistics

In the underlying study, 29 FinTech and Robo solutions have been found that claim to offer Machine Learning or Artificial Intelligence solutions whereas 21/29 suppliers do not specify their ML algorithms used in the business model. There are three suppliers (two FinTechs and one Robo) that use DL. Again, the concrete algorithm used is not revealed in detail. Furthermore, two websites have been found that offer various open-source codes of MLA that can be compared with each other for given standard applications in automated Asset Management services. Beside this, only three distributors have been found that specify their ML approach in more detail. *One company* uses cross-sectional graphs which is probably true for most ANNs, *the other company* utilizes feed-forward algorithm (which is also true for most ANNs) and *the third company* uses convolutional neural networks which is a DL algorithm mostly used in image and speech recognition but also finds application in reinforcement learning.[8]

To summarize our findings, the public available information on ML algorithms used in the FinTech and Robo scene is poor (see *figure 6*). This is probably because most of the suppliers are startups that do not want to lose their competitive advantage. Once the ML algorithm is named, it is quite easy with today's open-source software packages to copy their business model and become a competitor with less research and development costs.[9]

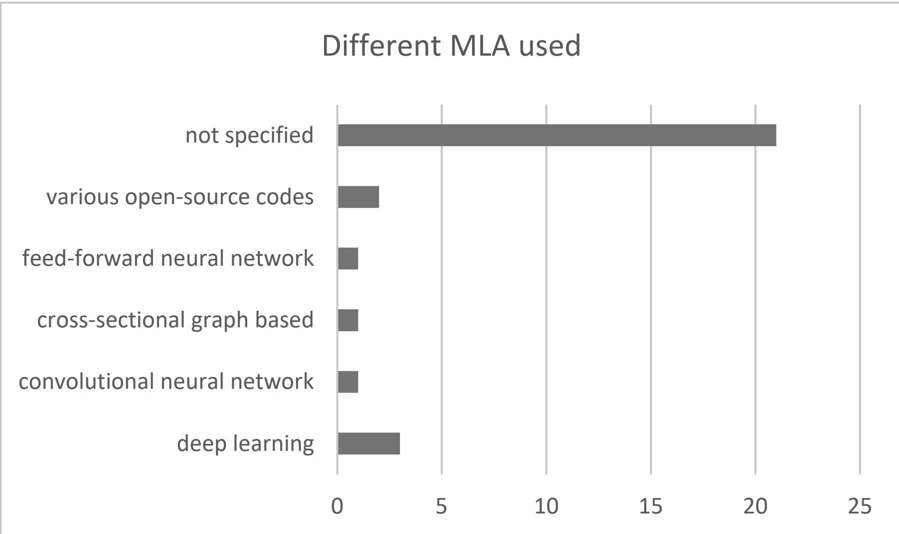

Figure 6: Machine Learning Algorithms used as published on FinTech and Robo Advisor websites (in absolute numbers).

Source: Own research 2020

8 Reinforcement Learning works by nudging the algorithm in form of human interaction, mostly by punishment or reward actions that refine the incentive function of the ML algorithm. Reinforcement has been prominently used in training DL models for playing AlphaGo, a game that cannot be solved by so-called brute force methods (compare *Silver et al.* 2016 and *Silver et al.* 2017).

9 For various programming languages, there are pre-defined software packages that offer state-of-the-art ML algorithms.

As can be seen in *figure 7* most suppliers offer at least two or three out of the five categories described in section 1.1. There are only two B2B suppliers that potentially aim to focus on all five categories, i.e. offering the complete range of Asset Management tasks.

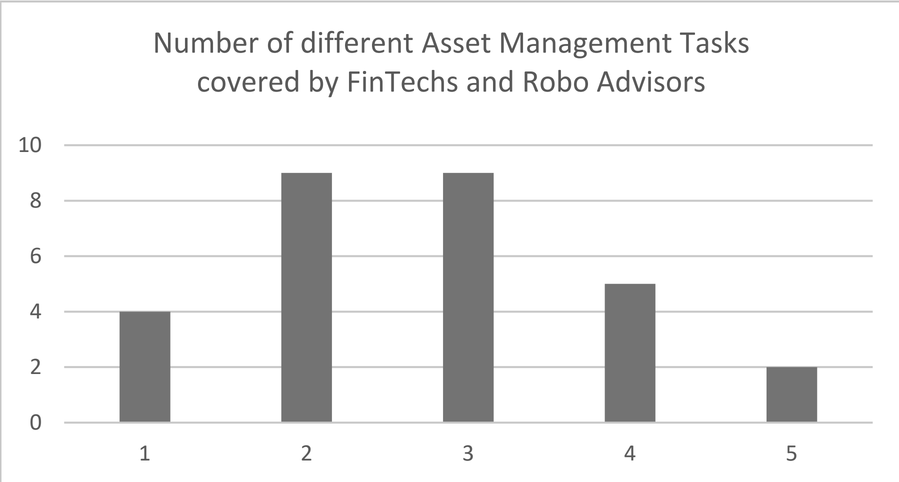

Figure 7: Number of different Asset Management tasks covered by a single FinTech/Robo supplier.

Source: Own research 2020

Figure 8 shows that the majority of tasks that are potentially suitable to ML algorithms point to the asset universe selection (i.e. 22 out of 79 supplier tasks in total, resulting in 28 % of total ML applications). This is not surprising since the process of asset selection resembles a classifier problem in which ML approaches find their predominant applications. In contrast only 5 out of 79 supplier tasks (around 6 %) deal with the identification of the investor profile, which is also not surprising since this task in Asset Management is based on very individual data with limited access. Perhaps sentiment analysis and an ever-growing data amount of social media data will change this picture in the near future. The remaining categories Portfolio Optimization (18 %), Rebalancing (23 %), and Performance Review (25 %) can be viewed as equally covered by ML solutions (due to the amount of small data available) since these categories are more or less inevitably linked to each other. Possibly, there is a slight trend towards Performance Review, which mirrors the suppliers' suggestion to fulfill the general "alpha criteria" in Asset Management.[10]

10 By „alpha criteria" we mean the Asset Manager's wish to beat the average market returns of the MSCI index for example which is around 6 %-9 % in recent years.

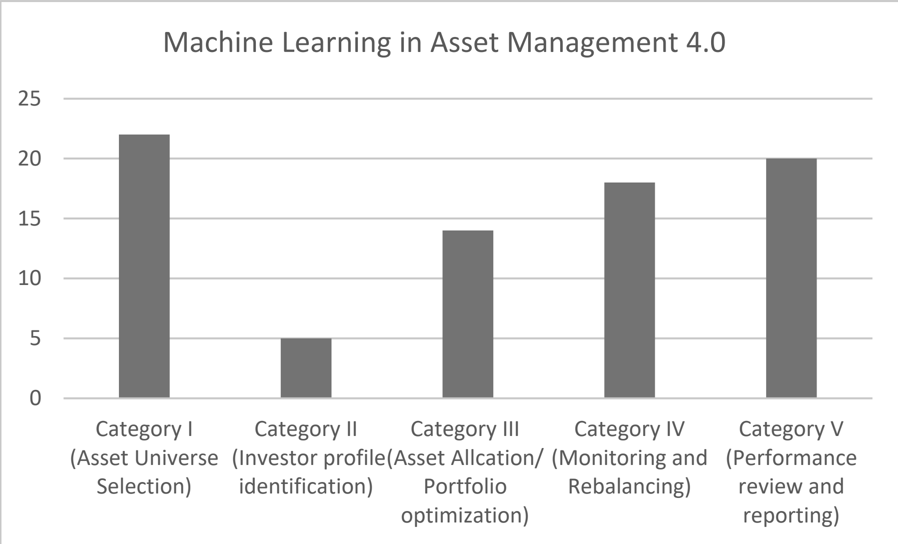

Figure 8: Asset Management tasks potentially covered by Machine Learning algorithms (in absolute numbers).

Source: Own research 2020

Based on the above research, there is currently no Robo solution, which combines Text Mining algorithms in a fully automated asset allocation system. We have identified two FinTechs in our sample that offer B2C solutions with sentiment analysis. The companies use Natural Language Processing (NLP) in combination with Deep Learning, like LSTM, in order to derive sentiment scores from financial newsfeeds. These sentiment scores are used as signals in early warning systems for further analysis and predictions on market movements.

Although we have not found any empirical evidence for RAs using Text Mining algorithms, we would like to highlight the importance for the inclusion of Text Mining from a model-based perspective. *Harrison/Pliska* (1981) as well as *Delbaen/Schachermayer* (1994) analytically show that, under the assumption of no arbitrage, market prices fulfill the fundamental martingale property. This implies that without the possibility of generating profit out of “nothing”, each asset price yields a conditional expectation of the risk-free interest rate under a synthetical probability distribution that is called risk-neutral or equivalent martingale measure. The conditional expectation under this martingale measure is built upon an information system, which is a conglomerate of all public available financial information like prices, news or financial reports. In the age of Big Data and internet newsfeeds, this information system grows exponentially with each period. When information is distributed unequally among market participants, information asymmetries arise, thereby effecting market prices (*Admati 1985*). *Biais et al.* (2010) show in a dynamic equilibrium model, that market separation as proposed by the CAPM will fail under information asymmetries, resulting in less optimal index portfolios. As consequence, uninformed investors structure their portfolios purely based on the information offered by market prices. They trade a mean-variance-efficient portfolio and cope with the winner’s curse problem, i.e. preventing them from the hazard of paying too much for certain assets due to increased optimism, which better informed investors do not share. On the contrary, informed investors are willing to pay a premium to protect themselves against endowment shocks. Further, they benefit from a more efficient investment based on their exclusive information on asset prices.

In this context, Text Mining and NLP systems, integrated into early warning systems of RA, would help to reduce information asymmetries for a wider community of market participants. A new equilibrium emerges with more informed investors who constantly seek to buy protection against possible market drawdowns, thereby stabilizing the financial system.

2.3 Legal limitations for using Machine Learning in Robo Advisory

A possible reason for FinTechs and RAs refusing MLA in their automated asset management processes could be found in the regulatory framework. According to the obligations set out in Article 25(2) of, and Articles 54 and 55 of MiFID II, investment firms providing investment advice or portfolio management have to provide "suitable" investment decisions. In contrast to this, MLAs especially based on DL, are generally viewed as Black Boxes (*Sjberg* 1995). Suitability in investment advice and intransparency in decision boundaries are therefore difficult to align. Even recent updates concerning the regulatory framework for Robo Advisors within the MiFID II context (Guidelines on certain aspects of the MiFID II suitability requirements) published by the European Securities and Markets Authority (ESMA) on 6th Nov. 2018 (ESMA 35–53–1163) do not include any reference to MLA.

Further, B2B as well as B2C RAs are audited and therefore have to prove their alignment with suitability (ML Audit).[11] Moreover, for the B2C sector, trust building factors play a crucial role when it comes to the adoption of RA services. We therefore need a measure of 'trust' to evaluate Robo AI decisions. Transparency solutions like LIME, promise to be model agnostic by approximating local decision boundaries (*Ribeiro et al.* 2016). Further approaches to verify and validate ANNs are found in *Taylor* 2006 as well as in *Montavon* 2018 who proposes Sensitivity Analysis (Sensi), Taylor Decomposition (TD), Layerwise Relevance Propagation (LRP) as transparency checks. In addition to this, regulatory guidelines have to be adjusted for the use of ML in RA. The full process can be summarized in figure 9. In

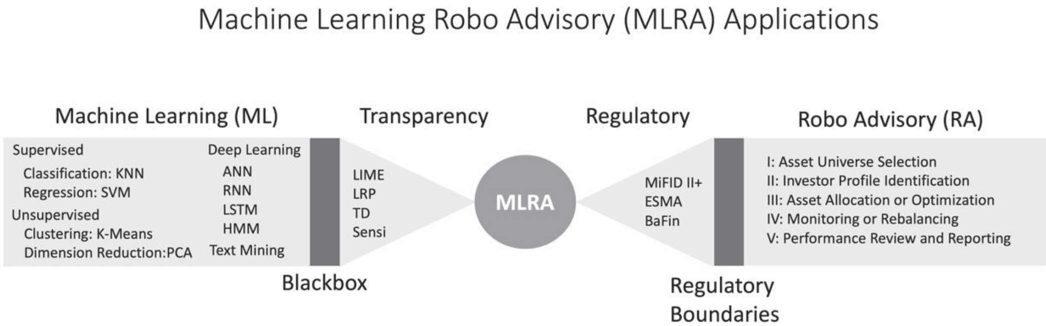

Figure 9: Synergy effects between regulated Robo Advice and transparent Machine Learning applications.

Source: Own illustration 2020

11 Note that in this sample the number of B2B companies offering AI solutions was very small, amounting four companies in total (with two FinTechs and two RAs each).

general, effective marketing campaigns and proven historical performance records are necessary to establish the trust to the AI methods in the RA sector.

Corresponding standards have already been discussed in *Weber/Rainer* (2016) as well as in *Baker (*2018). Authors like *Calo* (2017) and *Dafoe* (2018) discuss the general legal governance of AI (not specific to RA). To the best of our knowledge, there are no explicit regulatory guidelines for incorporating MLA within RA. Current ML applications are treated based on the current MiFID II guidelines. A future collaboration and open discourse among scholars, practitioners and regulators would be desirable (*Giudici* 2018). Furthermore, the German Data Ethics Committee (DEK) published general ethical guidelines for incorporating data based and algorithmic driven decision support systems, including AI (*DEK* 2019). According to these guidelines, current RA solutions must be subject to the following eight principles:

1) People-centered and value-driven design of technology.
2) Promoting digital literacy and critical reflection within the digital world.
3) Strengthening the protection of personal freedom, self-determination and integrity.
4) Promoting responsible uses of data that are compatible with the common good.
5) Risk-adapted regulation and effective oversight of algorithmic systems.
6) Preserving and promoting democracy and social cohesion.
7) Aligning digital strategies with sustainability goals.
8) Strengthening the digital sovereignty of Germany and Europe.

Especially regarding point 5), the regulator is directly addressed to take action and further strengthen the position of retail investors by highlighting the potential risks of algorithmic trading advice and by incorporating a decision control system to prevent ‘unsuitable’ investments.

2.4 Limitations of the underlying research design and outlook for future research

Due to the small sample size (29 FinTech and Robo solutions) the results should be treated carefully and may not be representative of the true nature of current existing ML solutions in the market. We therefore acknowledge the following major limitations:

- For this analysis, we chose the four main and most frequently used buzzwords ‘Machine Learning’, ‘Artificial Intelligence’, ‘ML’ and ‘AI’. Enriching the google site search with other classes of ML algorithms as presented in table 1 in the appendix or by trying out all forms of standard algorithms as already outlined in section 1.2 (e.g. DL, RNN, ANN, LSTM, HMM) did not lead to additional hits. However, the results might differ if the RA universe was enlarged.
- We did not choose to conduct a more intensive qualitative analysis, e.g. by creating a survey addressing RA and FinTech companies directly, since it was assumed that firms investing in AI would directly advertise for the use of new technology on their website.
- In case of an increasing adoption of ML in RA, web scraping tools could be employed to closer investigate the use of different MLAs throughout the asset allocation process. With more publicly available information, Text Mining algorithms could additionally be used to mine through the Whitepapers published by each RA company. However, in the current situation of low acceptance and missing transparency, using web scraping and Text Mining to further automate the search process does not seem to be promising.

Future research may be directed into the following areas:

- Beside the pure knowledge of investment firms using AI, it would be very insightful to conduct an empirical research by comparing different Non-AI-Robos with AI-Robos in a Backtesting environment. A closer look at the proposed risk-return tradeoffs of Robos should be taken, as part of a transparency analysis, to further check the alignment with current MiFID II suitability guidelines.
- Another challenge is to fine-tune the above presented MLAs into a fully running Robo solution by testing LSTM and HMM in combination with early warning indicators that are based on sentiment analyses.

3 Conclusion and Critical Acknowledgment

The analysis shows that there are only few FinTech and Robo Advisor solutions on the global market that offer Machine Learning solutions in their automated Asset Management distributions. The German and Swiss market serves in total about 31 % of global ML distributions within our sample. We subdivided the full Asset Management process into five different categories and highlighted potential application fields in which Machine Learning has the ability to further leverage the investment allocation process. The feasibility analysis is supported by use cases from daily business experience. The most promising synergy effects lie in the usage of Text Mining in the context of sentiment analysis used for monitoring and rebalancing purposes, or for performance forecasting. Embedded into early warning systems, Text Mining can help to reduce information asymmetries and enables protection buying against future market drawdowns. However, the ongoing digitalization of personal asset allocation is inevitably linked to an increased access of highly sensible data. As a result, current regulatory guidelines, like the MiFID II obligations, will have to follow up with the recent developments in Robo Advisory.

4 Appendix

Keywords and Alternative Formulations
AI driven, AI based, AI run
Predictive models relying on machine learning
Evolutionary Intelligence
Deep Learning
Sentient's Algorithm
Cross-sectional Graph-based Machine Learning
Neuronale Netze, Neural Networks
Feed-forward Neural Networks
Multiple Layer Autoencoder Setup
Reinforcement Learning
Convolutional Neural Network (CNN)
Self-learning algorithm
Artificial general intelligence (AIG)
Mimic's the human brain

Table 1: List of keywords inducing the use of AI in our RA's sample selection.

Source: Own research 2020

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