How Machine learning is affecting financial services.

Artificial intelligence (AI) and machine learning are being rapidly adopted for a range of applications in the financial services industry. As such, it is important to begin considering the financial stability implications of such uses. Because uses of this technology in finance are in a nascent and rapidly evolving phase, and data on usage are largely unavailable, any analysis must be necessarily preliminary, and developments in this area should be monitored closely

Researchers in computer science and statistics have developed advanced techniques to obtain insights from large disparate data sets. Data may be of different types, from different sources, and of different quality (structured and unstructured data). These techniques can leverage the ability of computers to perform tasks, such as recognizing images and processing natural languages, by learning from experience

This report defines AI as the theory and development of computer systems able to perform tasks that traditionally have required human intelligence. AI is a broad field, of which 'machine learning' is a sub-category.[7] Machine learning may be defined as a method of designing a sequence of actions to solve a problem, known as algorithms,[8] which optimize automatically through experience and with limited or no human intervention.[9] These techniques can be used to find patterns in large amounts of data (big data analytics) from increasingly diverse and innovative sources.

There are several categories of machine learning algorithms. These categories vary according to the level of human intervention required in labelling the data:

•In 'supervised learning', the algorithm is fed a set of 'training' data that contains labels on some portion of the observations. For instance, a data set of transactions may contain labels on some data points identifying those that are fraudulent and those that are not fraudulent. The algorithm will ‘learn’ a general rule of classification that it will use to predict the labels for the remaining observations in the data set.

•‘Unsupervised learning’ refers to situations where the data provided to the algorithm does not contain labels. The algorithm is asked to detect patterns in the data by identifying clusters of observations that depend on similar underlying characteristics. For example, an unsupervised machine learning algorithm could be set up to look for securities that have characteristics similar to an illiquid security that is hard to price.

With the growth of data in financial markets as well as datasets – such as online search trends, viewership patterns and social media that contain financial information about markets and consumers – there are even more data sources that can be explored and mined in the financial sector. On the demand side, financial institutions have incentives to use AI and machine learning for business needs. Opportunities for cost reduction, risk management gains, and productivity improvements have encouraged adoption, as they all can contribute to greater profitability. In a recent study, industry sources described priorities for using AI and machine learning as follows: optimizing processes on behalf of clients; working to create interactions between systems and staff applying AI to enhance decision-making; and developing new products and services to offer to clients.

There is also demand due to regulatory compliance. New regulations have increased the need for efficient regulatory compliance, which has pushed banks to automate[24] and adopt new analytical tools that can include use of AI and machine learning. Financial institutions are seeking cost effective means of complying with regulatory requirements, such as prudential regulations, data reporting, best execution of trades, and rules on anti-money laundering and combating the financing of terrorism (AML/CFT). Correspondingly, supervisory agencies are faced with responsibility for evaluating larger, more complex and faster-growing datasets, necessitating more powerful analytical tools to better monitor the financial sector.

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A number of developments could impact future adoption of a broad range of financial applications of AI and machine learning. These developments include continued growth in the number of data sources and the timeliness of access to data; growth in data repositories, data granularity, variety of data types; and efforts to enhance data quality. Continued improvement in hardware, as well as AI and machine learning software as a service, including open-source libraries, will also impact continued innovation. Development in hardware includes processing chips and quantum computing that enable faster and more powerful AI. These developments could enable cheaper and broader access to AI and machine learning tools that are increasingly powerful. They could make more sophisticated real-time insights possible on larger datasets, such as real-time databases of online user behaviour or internet-of-things (IoT) sensors located around the world.

Use of AI and machine learning for trading could impact the amount and degree of ‘directional’ trading. Under benign assumptions, the divergent development of trading applications by a wide range of market players could benefit financial stability. For example, if machine learning-powered robo-advisors give more customised advice to individuals, their investment activities may become more tailored to individual preferences and perhaps less correlated with other trading strategies. By reducing the barriers to entry for retail consumers to invest, these applications could also expand the investor base in capital markets. Similarly, the use of AI and machine learning for new and uncorrelated trading strategies by hedge funds could also result in greater diversity in market movements. More efficient processing of information could help to reduce price misalignments earlier and hence mitigate the build-up of macro-financial price imbalances. On the other hand, new trading algorithms based on machine learning may be less predictable than current rule-based applications and may interact in unexpected ways. To the extent that firms using AI or machine learning techniques can generate higher returns or lower trading costs, it is likely that incentives for adoption will increase. In the absence of data on the extent of market-wide use, market movements may be ascribed to AI and machine learning models, and interpretation of market shocks may be hampered. Finally, high frequency trading (HFT) applications of AI and machine learning could be new sources of vulnerabilities. If a similar investment strategy based on AI and machine learning is widely used in HFT, it might increase market volatility through large sales or purchases executed almost simultaneously.

Regarding leverage, liquidity, and maturity transformation, the adoption of AI and machine learning by financial market participants such as hedge funds and market makers may also have both positive and negative impacts. AI and machine learning could increase liquidity in financial markets through enhanced speed and efficiency of trading activities.

References.

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3.See EIOPA (2017); U.S. Federal Register (2017), Vol. 82, No.33, and Bureau of Consumer Financial Protection: Docket No. CFPB Notice and Request for Information Regarding Use of Alternative Data and Modelling Techniques in the Credit Process, February 21, 2017 (“CFPB RFI”); European Banking Authority (2017), “Report on innovative uses of consumer data by financial institutions, June. See also FSB FinTech Issues Group (2017),

OECD (2013), "Guidelines on the Protection of Privacy and Trans border Flows of Personal Data," July.[5] For instance, Articles 13, 14, and 15 require disclosure of the existence of automated decision-making, including profiling, referred to in Article 22(1) and