30th March 2022

AI and Machine Learning for Credit Rating Models – Part I

A brief overview of the regulatory landscape

AI and Machine Learning for Credit Rating Models

Regulators look towards AI and ML

With the exponential rise in Artificial Intelligence (AI) and emergence of 'Big Data', supervisors across the world share their views and recommendations on the safe adoption of AI and machine learning (ML) in financial services. In today's presentation, we take a quick look at supervisors' expectations on the application of AI and ML especially for credit rating models.

Regulatory landscape

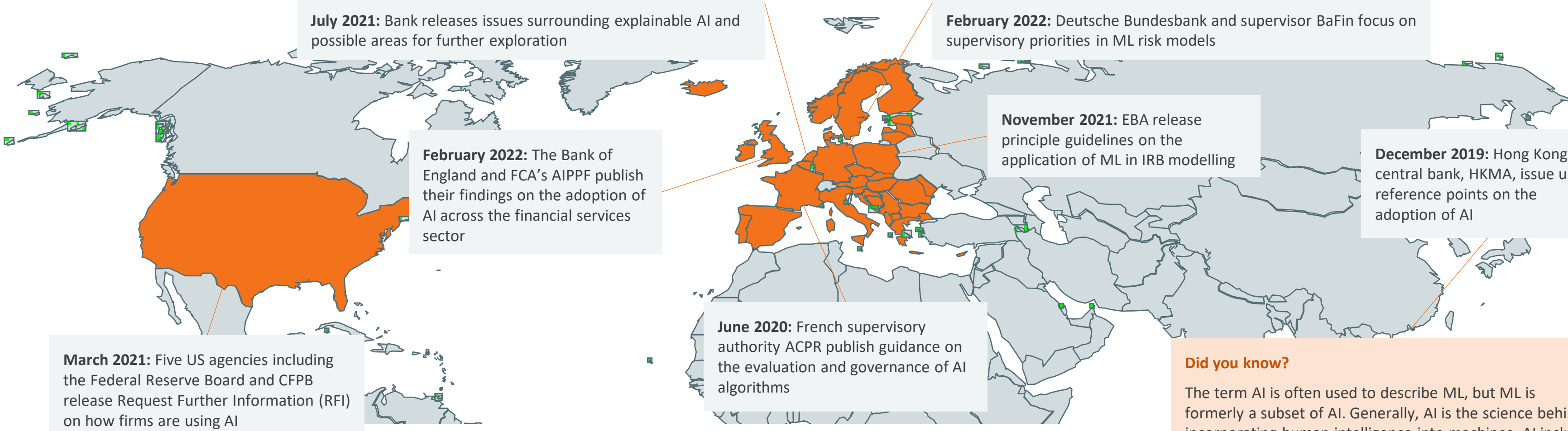
The adoption of AI continues to grow within financial services for purposes such as fraud detection, risk based pricing and credit decisioning.

However, the use of ML, a subset of AI, for prudential regulatory modelling namely internal-ratings based (IRB) modelling remains limited. Financial institutions have been wary of using ML algorithms for calculating own funds requirements largely because of the challenges associated with model interpretability.

To promote greater use of AI/ML in financial services including regulatory modelling, supervisors around the world issue guidance on the application of AI/ML.

Fintegral acknowledges the adoption of AI within financial services is currently of global interest. Therefore, we will look at four individual publications focused on the UK, Germany, Europe and Hong Kong.

There is a common theme across the articles with supervisors sharing similar views on the adoption of AI and ML, consequently helping to establish a clearer harmonised framework for firms.



July 2019: Dutch central bank De Nederlandsche Bank release principles on the use of AI in the financial sector

July 2021: Bank releases issues surrounding explainable AI and possible areas for further exploration

November 2020: German central bank Deutsche Bundesbank outline twelve considerations for AI and ML adoption

February 2022: Deutsche Bundesbank and supervisor BaFin focus on supervisory priorities in ML risk models

February 2022: The Bank of England and FCA's AIPPF publish their findings on the adoption of AI across the financial services sector

November 2021: EBA release principle guidelines on the application of ML in IRB modelling

December 2019: Hong Kong's central bank, HKMA, issue useful reference points on the adoption of AI

March 2021: Five US agencies including the Federal Reserve Board and CFPB release Request Further Information (RFI) on how firms are using AI

June 2020: French supervisory authority ACPR publish guidance on the evaluation and governance of AI algorithms

Did you know?

The term AI is often used to describe ML, but ML is formerly a subset of AI. Generally, AI is the science behind incorporating human intelligence into machines. AI includes both rule based and non-ruled based applications where ML falls under the latter. For AI adoption in credit rating models, we will specifically refer to ML based AI applications.

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Barriers to the adoption of AI and ML

The use of AI and ML for IRB modelling remains limited with the lack of model interpretability and risks of biased outcomes being significant stumbling blocks. These may be closely linked to the lack of in-house AI expertise and having insufficient quality data as majority of firms highlight these as key concerns. Furthermore, the application of AI may amplify existing risks.

Survey findings

The Bank of England and Financial Conduct Authority (FCA) conducted a joint survey[1] in 2019 to understand the current use of AI in UK financial services.

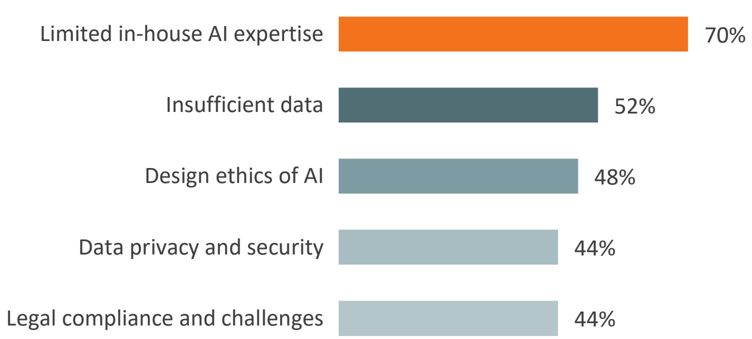
Similarly, the Hong Kong Monetary Authority (HKMA) conducted a survey[2] to understand the status of AI within retail banking in Hong Kong.

Both surveys showed significant overlap in identifying key barriers in the adoption of AI. The barriers identified are analogous to the challenges of ML for IRB modelling as identified in the European Banking Authority's (EBA's) recent discussion paper.

Current regulations aren't seen as barriers, but firms stressed further guidance and clarity on interpreting supervisory expectations is required. In addition, AI could potentially amplify existing risks – an opinion shared by the OECD[3] and the AIPPF[4].

The largest constraints to the adoption of AI are limited in-house AI experience leading to a lack of model explainability and risks of biased outcomes. Data quality and IT implementation challenges also pose risks to the adoption of AI.

What are the barriers affecting banks' adoption of AI?



Source: HMKA, 2019

Specific challenges in ML for IRB modelling

In their recent discussion paper, the EBA highlighted a number of challenges facing firms when adopting ML specifically for IRB modelling including:

- Limited understanding and interpretability of model results.
- Inadequate stakeholder engagement and understanding.
- Economic relationship between input and model outputs may not be clear.
- Model builders and validation teams may lack necessary skillset.
- Satisfying the CRR's 'use case' test (Article 144(1)(b) CRR).
- Biases and overfitting in the models may arise.
- Frequent updates to models will require assessing.

Did you know?

ML is an algorithmic based system with the ability to learn through experience without human intervention. Many, if not all, of the views and challenges in AI adoption apply to ML too.

[1] Bank of England, 2019, "Machine learning in UK financial services"
[2] HKMA, 2019, "Reshaping Banking with Artificial Intelligence"
[3] OECD, 2021, "Artificial Intelligence, Machine Learning and Big Data in Finance: Opportunities, Challenges, and Implications for Policy Makers"
[4] Bank of England and FCA, 2022, "The AI Public-Private Forum: Final report"

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EBA opens the door

In their recently published discussion paper[1], the EBA released a set of principle-based recommendations to support firms in the application of ML as primary IRB models.

Motivation for changes

The rise in popularity of ML has been driven by:

- Increased data availability, storage capacities and computing power.
- Improved predictive power and interpretability of internal models using ML.
- Inability of existing regression models to keep pace with the emergence of 'Big Data'.
- Openness to ML by regulators and supervisors.

EBA's principle-based recommendations

The following principle-based recommendations by the EBA are designed to help firms apply ML in their IRB model landscape:

- Ensure models are properly understood by their users including model builders, validation team and management functions.
- Avoid unnecessary complexity if not justified by a significant improvement in predictive power.
- Ensure models can be interpreted and documented clearly.
- Enhance the understanding of assumptions and behaviour of models on specific predictions, when using human judgement in model development and application respectively.
- Justify and monitor frequent updates of a model.
- Focus on validation which may require increased depth/frequency.

The aim of the recommendations will ensure:

- The capital requirements are set in a prudent manner which continue to be harmonised across Europe.
- The development of sophisticated ML models can coexist and adhere to the Capital Requirements Regulation (CRR).
- A consistent and clearer understanding of regulations.

Potential benefits

There are a number of potential benefits from the use of ML as primary IRB models. These include:

- Improved data quality in terms of more efficient data preparation and mining.
- Superior risk quantification and model discriminatory power for example by detecting useful predictive explanatory variables in large datasets or make use of non-linear relationships.
- Robust model validation and monitoring techniques for example by developing ML based model challengers to serve as benchmark to the standard models.

The EBA plans to release the outcome from its discussion paper once comments from participating firms have been reviewed. No date given on expected release.

[1] EBA, 2021, "Discussion Paper on Machine Learning for IRB Models" – EBA/DP/2021/04

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Bank of England and FCA explore the safe adoption of AI in financial services

After a year-long deliberation, the AIPPF[1] echoed many of the sentiments highlighted by the EBA and HKMA on the development and utilisation of AI highlighting three key areas of focus and providing best practice on data, model risk and governance[2]. Many of the risks highlighted in the application of AI are shared across financial services including risk management.

Data

The AIPPF illustrate proper data management being at the core of any robust and successful AI system.

- **AI begins with data:** The rise in 'Big Data' has rapidly increased the capabilities of AI by enabling more data to be made available.
- **Data quality:** Collation of data and identifying the attributes of the data including understanding their provenance, completeness and their relevance are ever so more critical in AI.
- **Unstructured data**: AI is expanding to various areas in financial services and the use of unstructured or 'alternative' data is becoming more prominent.
- **Data standards:** AI is changing the landscape of many organisations and therefore there is an increasing call for the development of AI specific data standards.

Model risk

As described earlier, most risks related to the use of AI within financial services are not new. However, the complexity involved in implementing AI can create new challenges as well as amplify existing ones.

- **Managing complexity:** The complex nature of AI models pose a number of challenges and relate to various factors including the the chosen variables, hyperparameters, economic intuition between inputs and outputs as well as the algorithms themselves.
- **Explainability:** Interpreting model outputs with clear concise reasoning to stakeholders is crucial.
- **Managing change:** The limited transparency in AI models mean they must be monitored on a frequent basis. This will allow users to assess the models are behaving in line with expectations and look to retrain when required.

Governance

The inherent autonomous nature of AI models gives rise to the need for further scrutiny and monitoring.

- **Foundation:** Existing governance and model risk management frameworks provide a sound foundation for AI models partly because AI models will habitually interact with other operations. In the Bank of England's 2019 survey[3], it found the majority of ML users were already leveraging on existing risk management frameworks.
- **Materiality:** The governance of AI models should reflect the risk and materiality of the model use case. For example, regulatory IRB models will likely be subject to further scrutiny due to their impacts on a bank's capital requirements.
- **Centralised body:** AI continues to be harnessed by multiple functions within financial institutions. Creating a single centralised governing body to uphold AI governance standards is recommended.

The Bank of England and FCA plan to publish a new discussion paper on AI later this year broadening the engagement with a wider set of stakeholders.

[1] The AI Public-Private Forum (AIPPF) was established by the Bank of England and FCA in 2020 to extend the dialogue between public, private and academic institutions on AI and how best to strengthen the understanding and adoption of AI.
[2] Bank of England and FCA, 2022, "The AI Public-Private Forum: Final report"
[3] Bank of England, 2019, "Machine learning in UK financial services"

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BaFin and Deutsche Bundesbank consult stakeholders

German financial supervisor BaFin and central bank Deutsche Bundesbank highlight the impetus to adopt ML must come from institutions themselves. Existing risk regulations are prescribed currently in a technology-neutral manner providing a sufficient framework for ML. The central bank also released their 12 considerations and potential supervisory expectations for ML.

Key points

German financial supervisor BaFin and central bank Deutsche Bundesbank focus on the characteristics and supervisory priorities in ML based risk models. They highlight the following in their latest consultation[1] on this subject:

- The impetus to adopt ML must come from institutions themselves. Supervisors do not promote the use of ML methods as long as traditional methods of meeting regulatory requirements are considered still suitable.
- Pillar 1 already includes extensive regulations for reviewing and approving internal models formulated in a technology-neutral manner and providing a sufficient framework for ML.
- Emphasis must be on good data quality and management for ML to succeed. Data must be representative and the use of ML methods would therefore not be grounds for any new or special requirements.
- The trade off between higher model predictive ability and comprehensibility of the model must be considered and weighed up against potentially greater model risk.
- The majority of respondents in their consultation believe that not every intermediate step needs to be explainable, but only the final output.
- Frequent adjustments of ML models make it difficult to distinguish between model adjustments and model changes and may require justification.
- Supervisory authorities are requested to further refine the definition of model change as well as generally speed up model approval processes in order to avoid creating competitive disadvantages.

The 12 considerations for ML by Deutsche Bundesbank[2]					
1	Leverage existing frameworks	5	Identify AI characteristics	9	Data quality is key
2	ML should be assessed case by case	6	Outsourced ML still needs to be supervised	10	Rigorous validation required
3	Prudential mandate doesn’t cover ethical issues	7	Black box is not a ‘no go’	11	Supporting processes are ever more important
4	Supervisors focus is not on ML algorithm itself but its application	8	XAI has its downfalls too	12	Learning frequencies need to be justified

[1] BaFin and Deutsche Bundesbank, 2022, “Machine learning in risk models consultation paper. Responses to the consultation paper”
[2] Deutsche Bundesbank, 2020, “The Use of Artificial Intelligence and Machine Learning in the Financial Sector”

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Conclusion and next steps

Supervisors around the world are increasingly promoting the use of AI and ML in financial services in particular prudential risk modelling to help fast track adoption. Many of the articles reviewed share similar views with strong data quality and a robust governance framework crucial to successfully adopting AI.

Key takeaways

In this presentation, we have gained a partial insight into the minds of supervisors in the pursuit of safe adoption of AI and ML. The use of AI/ML for prudential regulatory modelling remains at an embryonic stage. Many of the papers discussed illustrate a common theme with the key takeaways as follows:

- The trade off between higher model predictive ability and model explainability must be considered.
- Strong data management and a robust governance framework are core to success.
- Supervisory focus is not on the ML algorithm itself but on its application.
- The intention to employ AI must be driven by firms themselves.
- Current risk-oriented regulations are written in a technology-neutral manner to promote innovation.

However, the application of AI and ML gives rise to potentially new financial and non-financial risks, as well as amplify existing vulnerabilities including:

- Lack of model explainability
- Risk of biased outcomes
- Limited in-house AI experience
- Insufficient good quality data
- IT implementation challenges

Category	Factors to consider	Difficulty[1]
Data	Sufficient quality data	●●○
	Data privacy and security	○○○
	Operational processes and IT	●●○
Modelling	Model design	●●○
	Design ethics	●●●
	Model explainability	●●●
Governance	Governance framework	●○○
	Model robustness and resilience	●●○
	Legal compliance	●●○
	Training and development of staff	●○○
	Stakeholder engagement	○○○

Low ○○○ High ●●●

Next steps

We await the EBA's findings from its consultation on ML for IRB modelling, plus the Bank of England and FCA's consultation on AI expected to be released later this year.

In the next part(s) of our series on AI and ML for credit rating models, we will look at:

- A technical comparison between 'traditional' IRB regression models vs ML based IRB models.
- Methods to overcome some of the risks associated with AI and ML in credit rating models.

[1] The difficulty ranking illustrates the potential difficulty in implementing a particular factor in the pursuit of AI and ML adoption for prudential purposes. This does not imply lower difficulty factors are 'less' important or relevant. For example, data privacy is crucial, however, most firms will already have a robust data management framework in place, therefore, the application of AI/ML is not likely to pose a significant impact to a firm's operations.

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