Box 2.6

BANKING APPLICATION OF MACHINE LEARNING TECHNIQUES IN INTERNAL RATINGS-BASED MODELS. SUPERVISORY APPROACH

The last five years have seen a growing use of artificial intelligence techniques —and, in particular, machine learning (ML) — for credit risk measurement and management. The implementation of this type of methodology is still a minority in industry, but its possibilities have aroused great interest and there is a continuous upward trend in its use. In addition to enabling the exploitation of new data sources, one of the major benefits of these models is their capacity to provide more accurate risk estimates.

In certain cases, financial institutions are incorporating ML techniques into credit risk models, where they play a central role, mainly scoring or rating counterparties based on their risk. Since 2018, there have been examples in the Single Supervisory Mechanism (SSM) of the use of these advanced techniques in models that have been approved. As well as in credit risk, ML is also being used in other financial risks, such as market and counterparty risk, or in the context of Pillar 2.

On the supervisory side, there is a degree of caution as to the use of ML in internal ratings-based (IRB) models for the calculation of capital requirements, mainly due to the difficulty in interpreting and explaining such techniques, which are sometimes referred to as "black boxes" precisely because their greater complexity limits the ability to understand how the results are arrived at. In this regard, it should be noted that understanding the internal behaviour of a model and how it generates forecasts is necessary to ensure its alignment with economic logic and to allow, where appropriate, manual adjustments to the ratings (overrides).

At present, supervisory and regulatory bodies are working intensively in this field, promoting communication with stakeholders to ascertain the degree of maturity of these approaches, to find out which types of developments the institutions are planning to undertake and to clarify regulatory expectations.

There is also significant interest among Spanish institutions in the use of ML techniques, and several initiatives have been developed for their use as a central part of IRB models, the approval of which has involved the dedication of supervisory resources. It is worth noting that, in several of the models presented, the difficulty in interpreting the model's internal logic has been addressed by introducing constraints into the models. In any case, while the introduction of such constraints provides valuable insight into the functioning of the model, it does not by itself completely resolve the "black box" problem.

The application of ML techniques in the area of credit risk is not confined to capital estimation models; it is also generating interest in loan origination areas, where the greater predictive capacity as compared to traditional techniques would have a direct economic impact on institutions. Such uses will have a specific regulatory framework under the AI Act, but they are also subject to the requirements set out in the general data protection regulation. Among other issues, this regulation addresses personal data exploitation and the prevention of discriminatory bias, which can be a challenge when using such techniques.

The emergence of ML in credit models is an interesting challenge. Through its supervisory function, the Banco de España will be able to examine firsthand how these techniques penetrate the banking environment, and will monitor their repercussions on management tasks and on access to credit. Moreover, it will require the update of professional profiles and an even greater involvement in training and research to understand both the capabilities and limitations of this disruptive technology.

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1 ML is a field of artificial intelligence that generates knowledge from big data processing.

2 As well as being useful in terms of management, this scoring or rating serves as a first step in many internal ratings-based (IRB) models to define sets of counterparties with a similar level of risk and, subsequently, quantify their risk. In addition to these scoring processes, there are also other uses with a more secondary role, for example, the initial processing of the data.

3 A survey is currently being conducted by the ECB, in addition to the survey in the European Banking Authority's Discussion paper on machine learning for IRB models.

4 In this way, certain patterns in the variables are imposed in advance, which favours alignment with economic or business logic. For example, the relationship between the borrower's income and the probability of default is always forced to be negative.

5 Regulation of artificial intelligence, which specifies various requirements for the use of ML techniques in the granting of credit, as it is considered an essential service for individuals.