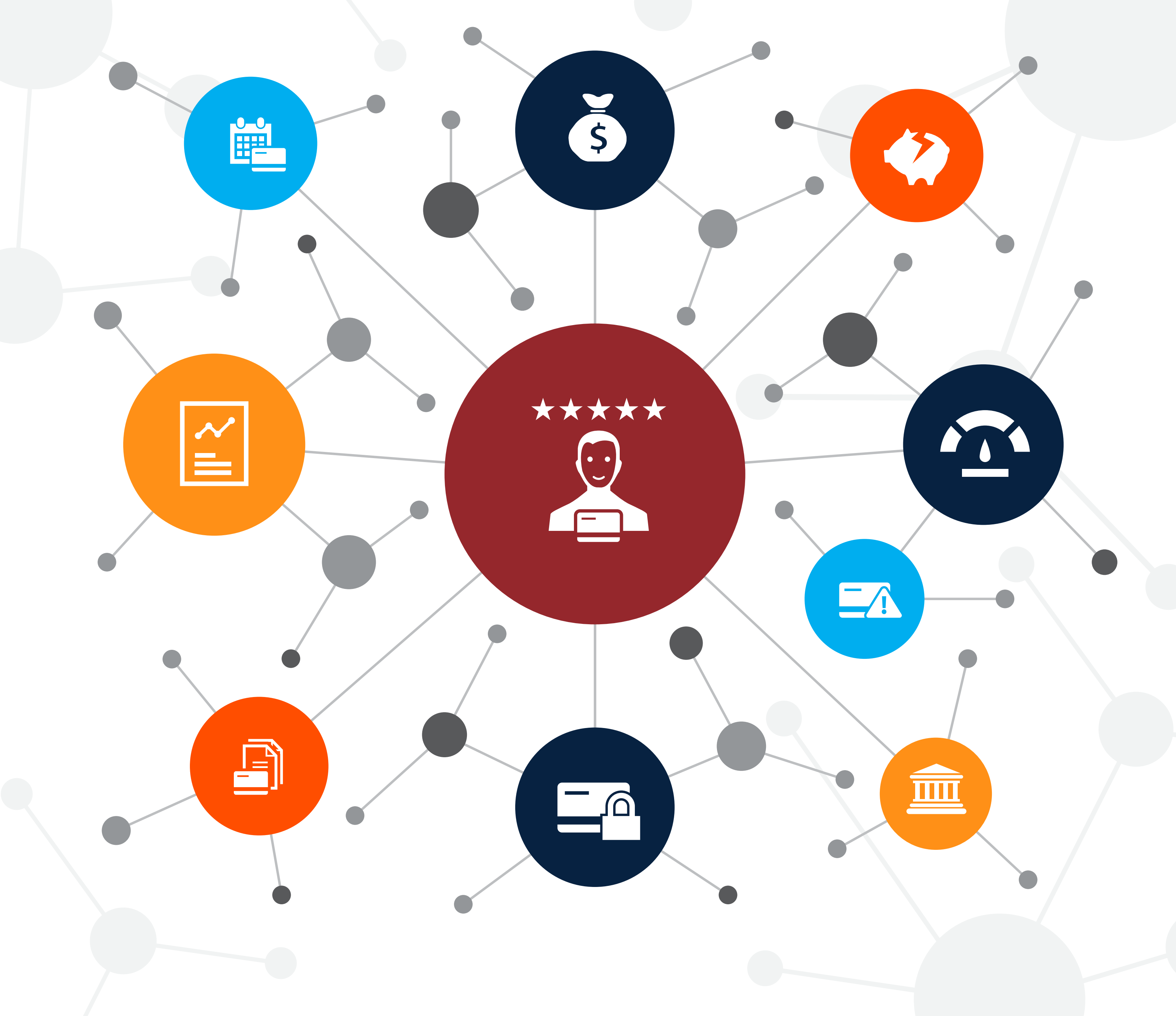

CREDIT SCORING APPROACHES GUIDELINES

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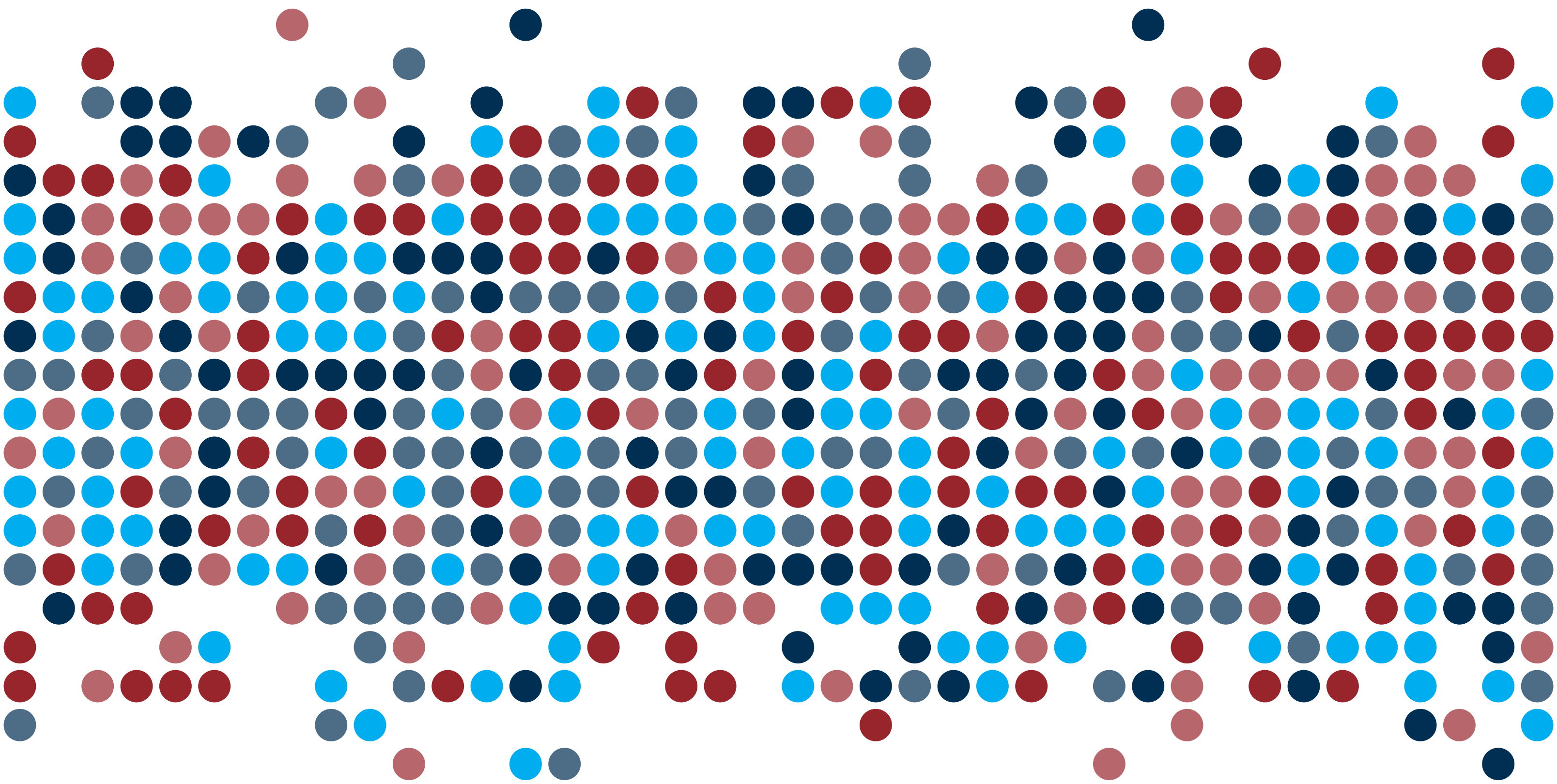


EXECUTIVE SUMMARY

Credit scoring is widely understood to have immense potential to assist in the economic growth of the world economy. Additionally, it is a valuable tool for improving financial inclusion; credit access for individuals and micro, small, and medium enterprises; and efficiency.

The use of credit scoring and the variety of scoring have increased significantly in recent years owing to better access to a wider variety of data, increased computing power, greater demand for improvements in efficiency, and economic growth.

Furthermore, the application of credit scoring has evolved from traditional decision making of accepting or rejecting an application for credit to inclusion of other facets of the credit process such as the pricing of financial services to reflect the risk profile of the consumer or business and the setting of credit limits. Credit scoring is also used to determine minimum levels of regulatory and economic capital, support customer relationship management, and, in certain countries, solicit prospective consumers and businesses with offers.

The methods used for credit scoring have increased in sophistication in recent years. They have evolved from traditional statistical techniques to innovative methods such as artificial intelligence, including machine learning algorithms such as random forests, gradient boosting, and deep neural networks. In some cases, the adoption of innovative techniques has also broadened the range of data that may be considered relevant for credit scoring models and decisions.

The opportunities of using innovative methods for credit scoring include greater financial inclusion and access to credit, improvement in the accuracy of the underlying models, efficiency gains from the automation of processes, and potentially an improved customer experience.

The use of innovative methods for credit scoring, however, also raises concerns about data privacy, fairness and potential for discrimination against minorities, interpretability of the models, and potential for unintended consequences because the models developed on historical data may learn and perpetuate historical bias. That said, there are also risks to consumers and businesses from a lack of innovation in credit scoring if it hinders improvements in financial inclusion and risk assessments.

There are also concerns about the effectiveness of credit scoring methods and technologies. These concerns apply especially in markets with weak or no adequate regulatory oversight or industry codes to regulate the conduct of credit services providers (CSPs).

The guideline recognizes that the technologies supporting innovative credit scoring are still evolving and that differences in use, accuracy, and robustness exist across markets. For example, in emerging markets, CSPs may still be operating on the basis of the credit officer's individual judgment, judgmental scorecards, or using traditional regression models at most. The talent and data infrastructure required to execute the more innovative approaches are still very limited in many markets. The guideline encourages the adoption of a human-centric approach, where innovation is applied with the human in mind.

This guideline proffers seven policy recommendations to guide on credit scoring, encompassing both models and decisions, in an effort to help regulators in their oversight roles and to aid in promoting transparency. The policy recommendations are as follows:

1. A legal and ethical framework is required to govern and provide specific guidance to credit service providers (CSPs).

2. The decisions made on the basis of credit scoring should be explainable, transparent, and fair.

3. Data accountability practices should be strengthened.

4. Credit scoring models should be subject to a model governance framework.

5. Collaboration and knowledge sharing should be encouraged.

6. The regulatory approach should strike a balance between innovation and risk.

7. Capacity building of regulatory bodies and within CSPs is essential.

ABBREVIATIONS AND ACRONYMS

ACCIS	Association of Consumer Credit Information Suppliers
AHP	analytic hierarchy process
AI	artificial intelligence
API	application programming interface
BIS	Bank for International Settlements
BCBS	Basel Committee on Banking Supervision
CART	classification and regression trees
CBDE	cross border data exchange
CEBS	Committee of European Banking Supervisors
CFPB	Consumer Financial Protection Bureau
CRA	credit reporting agency
CRSP	credit reporting service provider
CSP	credit services provider
CSA	Cyber Security Agency
DNN	deep neural network
EAD	exposure at default
EBA	European Banking Authority
ECB	European Central Bank
ECL	expected credit loss
ECOA	Equal Credit Opportunity Act
EDPA	European Data Protection Supervisor
EDPB	European Data Protection Board
ESMA	European Securities and Markets Authority
EU	European Union
FCRA	Fair Credit Reporting Act

FRB	Federal Reserve Board
FRS	Federal Reserve System
FSB	Financial Stability Board
FVTPL	fair value through profit and loss
G-10	Group of Ten
G-20	Group of Twenty
GDP	gross domestic product
GDPR	General Data Protection Regulation
GPFI	Global Partnership for Financial Inclusion
IAS	International Accounting Standards
IASB	International Accounting Standards Board
ICE	individual conditional expectation
IFRS	International Financial Reporting Standards
IOSCO	International Organization of Securities Commissions
LGD	loss given default
LIME	local interpretable model-agnostic explanations
MAS	Monetary Authority of Singapore
MLP	multilayer perceptron
MSMEs	micro, small, and medium enterprises
NLP	natural language processing
OCC	Office of the Comptroller of the Currency
PDPC	Personal Data Protection Commission (Singapore)
PD	probability of default
PD	partial dependence
PR	precision-recall
PSD 2	revised Payment Services Directive
ROC	receiver operator characteristic
SPPI	Solely Principle Payments and Interest
SVM	support vector machine
TRIM	Targeted Review of Internal Models

GLOSSARY

Alternative data

Information gathered from nontraditional data sources. Examples may include geolocation data, point-of-sale transactions, device data, and social media posts.

Cascading risks

Scenario where a single error is amplified or leads to a chain reaction in downstream processes owing to the interconnectedness of systems.

Credit rating

Numerical expression representing the credit worthiness of an entity.

Credit scoring

Form of statistical analysis that provides an estimate of the probability that a loan applicant, existing borrower, or counterparty will default or become delinquent.

Credit reporting service provider

Entity that administers a mechanism enabling credit information collection, processing, and further disclosure to users of data as well as value added services based on such data.

Credit services provider

Entity that provide loans and other forms of credit to consumers and businesses. It includes financial institutions, banks, financial technology providers, and alternative lenders.

Overfitting

Scenario where the analysis corresponds too closely to a particular set of training data, resulting in a failure to predict future observations accurately.

Precision-recall curves

Illustration of a summary of the trade-off between precision (y-axis) and recall (x-axis) at different probability thresholds.

Precision

Measure of the relevancy of a result. It is calculated as the number of true positives divided by the sum of the number of true positives and false positives.

Recall

Measure of the relevancy of how many truly relevant results are returned. It is calculated as the number of true positives divided by the sum of the number of true positives and false negatives.

Receiver operating curve

Graphical plot that represents the diagnostic ability of a binary classifier as its discrimination threshold varies. It is created by plotting the true positive rate against the false positive rate at different settings of threshold values.

Semistructured data

Form of structured data that does not conform with the structure of data models associated with relational databases. It contains tags or other markers to enforce hierarchies of records and fields within the data.

Structured data

Any data that reside in a fixed field within a record or file. Typically, the data reside in the form of relational databases and spreadsheets. The formal structure allows one to easily enter, store, query, and analyze the data.

Unstructured data

Data that do not have a predefined data model or are not organized in a predefined manner. They exist typically in the form of text files, images, social media data, and sensor data.

POLICY RECOMMENDATIONS

Policy Recommendation 1: A legal and ethical framework is required to govern and provide specific guidance to credit services providers (CSPs).

Where not done yet, regulatory bodies should put in place a legal and ethical framework that provides for appropriate oversight and responsible use of credit scoring. An ethical framework upholds fundamental human rights and ethical principles and incorporates a CSP's values and codes of conduct, while also ensuring that the legitimate interests of the CSPs can be met. The framework should also consider the protection of consumer rights and data privacy aspects.

Policy Recommendation 2: The decisions made on the basis of credit scoring should be explainable, transparent, and fair.

CSPs should understand and be able to explain to consumers the lending decisions made on the basis of credit scoring. CSPs should be able to understand and explain to regulatory bodies the way credit scoring is incorporated into their processes and the logic involved in its functioning. The data used, and the decisions made on the basis of credit scoring, should operate within equal opportunity or anti-discrimination laws (for example, to not use characteristics considered protected such as race and religion).

Explainable and Transparent Credit Scoring Decisions for Consumers

Consumers should receive enough information on the data used and the decisions made on the basis of credit scoring methods. The focus should, however, not be on the direct or indirect disclosure of the algorithm, but rather on the rationale behind the credit risk decision. Disclosure of the algorithm may infringe on proprietary rights, could lead to compromising its accuracy, and also may not be meaningful to the consumer. Organizations should consider providing the data subjects with an avenue to request a review of decisions that were fully automated and a correction of underlying inaccurate data (if this resulted in their credit score being impacted).

There is also a need to be transparent to consumers about the data collection process. The mechanisms should provide consumers with the key facts about data origin, the potential users and uses, any dispute resolution mechanisms, and the lawful use of personal data. If the data are used for a purpose other than that specified during data collection, within the boundaries of country-specific legislation, the lawful collection of data is required. If traditional or alternative data are used, consumers and regulators should have the right to know the source from where the data were extracted. The guidance also applies to cross-border data flows.

Explainable and Transparent Use of Credit Scoring

CSPs should be able to explain to regulators the way the credit scoring is incorporated into their processes and the logic involved in its functioning. CSPs should be able to quantify, explain, and adopt adequate measures to mitigate unintentional and potentially amplified risks associated with the use of credit scoring methods when appropriate and do so proportionately to the magnitude of the risks.

In cases where algorithms are not easily explainable (yet are parsimonious and justifiable), additional steps should be taken to verify that the input data, algorithms, and outputs are performing within expectations.

Policy Recommendation 3: Data accountability practices should be strengthened.

Recognizing the increasing risks of cyber security, data privacy, and consumer protection violations, owing to digitalization, industry participants should put in place sufficient controls to ensure data integrity and privacy. CSPs should understand the source of data and the way data are collected, updated, and improved over time.

Security of Data

CSPs should put in place sufficient controls and preventive measures against cyber attacks. Regulatory authorities should consider putting cyber laws in place that include punitive measures in cases of data breaches. There is a need for regular risk assessments, swift response, and reporting of incidents occurring in-house or at outsourced services providers.

Data Privacy and Consumer Protection

CSPs should integrate data privacy into the design process when building credit scoring methods. Privacy impact assessments will ensure that personal data are not used unlawfully without the permission of the consumer. In addition, the consumer should be accorded the rights to correct, to object to the use of their personal data for specific purposes, and to transfer or request deletion of information, subject to country-specific legislation.

Accountability in Data Usage

CSPs should specify the sources of data used for credit scoring in accordance with the rights of consumers and businesses. This practice is especially important in the cases of third-party data sources and alternative data. There should be clear audit trails on the use of data for credit scoring; the data flow from the original source needs to be clearly identified. This approach may include checks for types of data (proprietary or nonproprietary) and the accuracy of the data used.

Policy Recommendation 4: Credit scoring models should be subject to a model governance framework.

Credit scoring models, developed using both traditional and innovative techniques, should be subject to an effective model governance framework that considers, but is not limited to, the management of model risk, including the conceptual soundness of the model; assessment of unintended consequences such as cascading risks and the disregard of protected characteristics (for example, race, gender and religion); model ownership within a business context; and regular reviews and back-testing of models, including validation of model performance such as receiver operator characteristic (ROC) curves and/or precision-recall (PR) curves.

Policy Recommendation 5: Collaboration and knowledge sharing should be encouraged.

Sharing of Data

To the extent possible, collaboration between industry, governments, and regulatory bodies should be encouraged. Access to data plays a vital role in innovation and should be encouraged by regulatory bodies. To this end, regulatory authorities should consider implementing collaborative models such as open banking as a way of fostering innovation. Public policy should broadly encourage wider and timely availability of private and publicly held data, while ensuring full protection of personal data.

Sharing of Knowledge among Stakeholders

In addition to increased investments in research and the study of significant trends, regulatory bodies should publish their research and encourage independent study by industry and academic bodies to increase knowledge and understanding and deepen research on ethical aspects and transparency of innovative credit scoring methods. The collaboration and sharing of best practices among industry peers may help create and foster industry best standards.

Financial literacy

There is a need to ensure that consumers are educated and made aware about the uses of credit scores. Financial literacy, numeracy, and capacity go hand in hand with financial inclusion.

Policy Recommendation 6: The regulatory approach should strike a balance between innovation and risk.

Regulators need to strike a balance between harnessing the opportunities presented by credit scoring and mitigating risks. Financial integrity and data privacy should be protected. For example, consumers need to be protected from discriminatory decisions, while innovation should be encouraged. Improved practices in risk assessments may improve the accuracy of the risk weighting of assets and aid supervision. In addition, the impact of regulations on the development and adoption of innovative credit scoring and financial inclusion should be carefully considered.

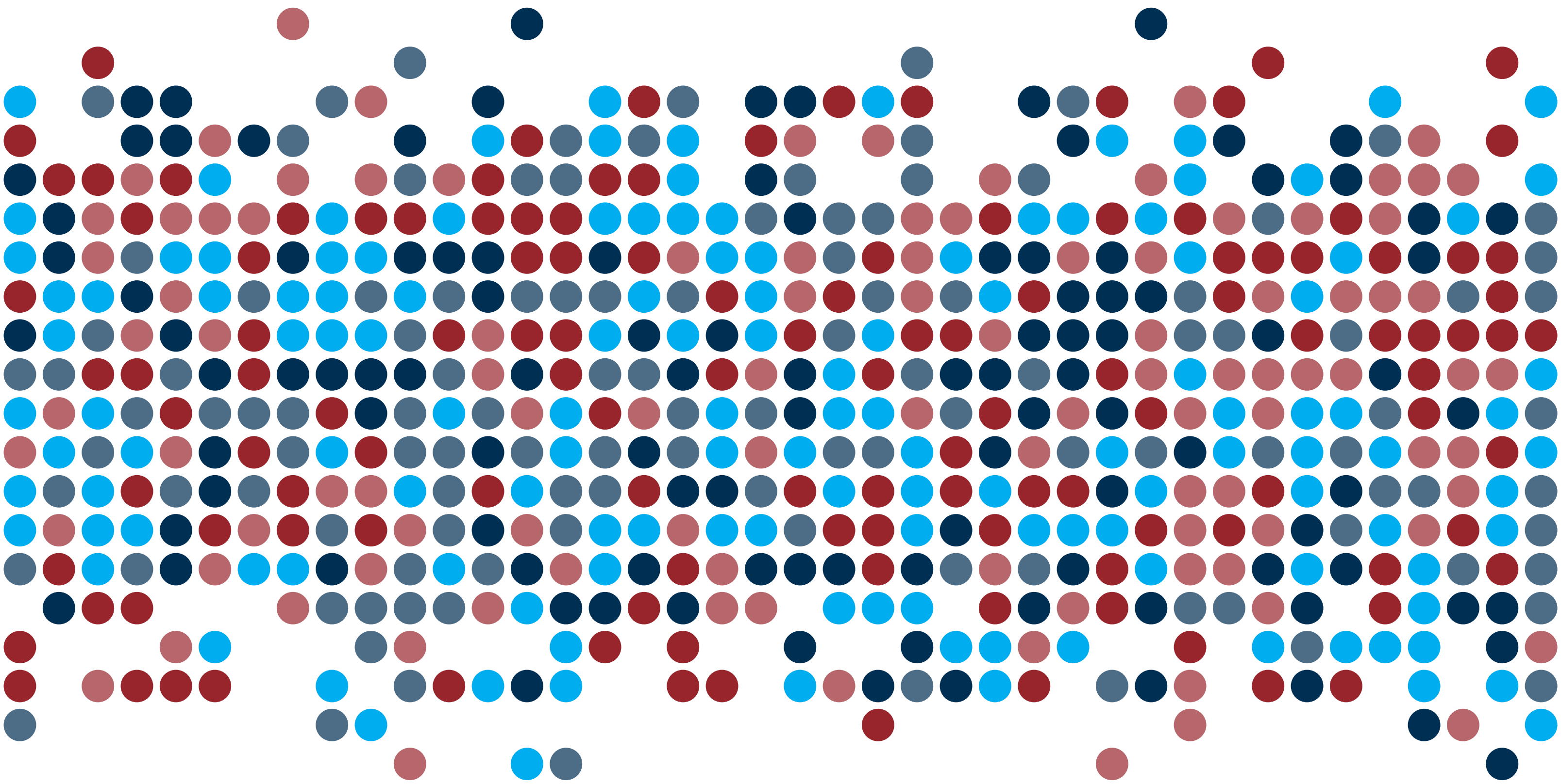
Policy Recommendation 7: Capacity building of regulatory bodies and within CSPs is essential.

Regulatory bodies should embrace an openness to change and an awareness that attitudes and practices are still evolving. Concretely, they should establish frameworks for innovation, such as regulatory sandboxes to support organizations that are developing products and services that use personal data in innovative ways, while also ensuring a safe and protected testing environment.

There should also be measures for capacity building and skills development within Regulatory bodies, in order to understand and supervise models and new innovations.

There is a need for heightened open and transparent communication that will help develop trust and confidence in the adoption of new technologies Meanwhile, rules need to be in place to ensure transparency and consistency.

Furthermore, the organizational setup, resources, and infrastructure capacity should be facilitated within CSPs. Dedicated focus on credit scoring should be supported with sufficient experts and technology. Coherent and well-connected working groups should be part of the development and assessment process of credit scoring methods.



1. BACKGROUND

Introduction

The uses of credit scoring methods have increased significantly in recent years, owing to access to data, rise of computational power, regulatory requirements, and demand for efficiency and economic growth (Demirguc-Kunt, Klapper, and Singer 2017).

Furthermore, the application of credit scoring has evolved from the traditional decision making of accepting or rejecting an application for credit to the inclusion of other facets of the credit process such as the pricing of financial services to reflect the risk profile of the consumer, setting of credit limits and regulatory capital, customer relationship management, and, in certain countries, targeting of prospective customers with offers.

In some cases, the use of sophisticated credit scoring methods has increased from traditional statistical techniques such as linear discriminant analysis and logistic regression to innovative methods such as artificial intelligence, including machine learning such as random forests, gradient boosting, and deep neural networks.

The adoption of innovative methods has increased in many cases not only the sophistication of the credit scoring methods but also their opaqueness. Unlike traditional credit scoring models, innovative methods are often viewed as challenging to interpret and explain (FSB 2017). In addition, innovative methods are prone to overfitting (that occurs when the analysis corresponds too closely to a particular set of training data, resulting in a failure to predict future observations accurately) and raise concerns about fairness and discrimination against minorities (European Commission 2018b).

The adoption of alternative modelling techniques has also broadened the range of data that could be considered relevant for credit scoring models and decisions. For example, credit services providers (CSPs) are now leveraging nontraditional data sources to score consumers and businesses with limited credit bureau information. The use of alternative data, such as granular transactional data in decision processes, however, has aroused increased interest from data privacy advocates. Likewise, regulators have taken a keen interest in the application of credit scoring, because of its potential implications for national financial systems and the broader goal of financial inclusion.

There are concerns about the effectiveness of credit scoring and technologies. This is especially true in markets where there is little or no adequate regulatory oversight or industry codes to regulate the conduct of CSPs.

Evolution of Credit Scoring

In the early days of credit reporting, CSPs used credit reports to offer financial services to consumers, businesses, and large corporations. Credit reports provided information about the consumer or business's demographics, insurance, and other utilities (Aire 2017).

The scientific background to modern credit scoring was pioneered by the statistical technique of discriminant analysis, devised by Ronald. A. Fisher (Fisher 1936). Discriminant analysis is a statistical technique used to differentiate between groups in a population through measurable attributes when the common characteristics of the members of the group are unobservable. In 1941, Durand recognized that the same approach could be used to distinguish between good and bad loans.

One of the first credit scoring algorithms was developed using linear programming (myFICO 2018). Initially, both the variables selected and the scores assigned were mainly judgmental. However, the systematic application of the scoring method contributed to consistency in the credit applications process. This approach became the start of using statistical methods to determine creditworthiness in an organized and transparent manner.

Small credit reporting companies, referred to as credit reporting service providers (CRSPs) in this guideline, developed into larger organizations that kept more accurate information. In 1970 in the United States, the Fair Credit Reporting Act (FCRA) was passed requiring CRSPs to open their files to the public; ensure discriminatory data including race, gender, and disability are not used for credit decisions; and delete negative information after a specified period (Federal Register 2011). Overall, computer technology, market forces, and the FCRA provided CRSPs with the impetus to transform themselves from small cooperatives to large scale CRSPs (Furletti 2002).

CRSPs can exist as either credit bureaus or credit registers. Credit bureaus are typically privately owned companies that collect information from financial and nonfinancial entities, including microfinance institutions, and provide credit information to CSPs. Credit registries tend to be public entities managed by supervisors or central banks (World Bank 2016a).

Ultimately, the economics of processing a high volume of loan applications, along with the improvement of the predictive power of the models and the constant advances in available computing power, lead to the acceptance of statistically based, automated scoring systems worldwide.

Credit scoring methods that use innovative algorithms are designed to speed up lending decisions, while assessing risk more accuratel—CSPs have long relied on credit scores to assess risk when making lending decisions for consumers and businesses. Historically, to capture the willingness and ability of the borrower to repay, data on past payment history served as the foundation of most credit scoring models (Federal Register 2011). These models have traditionally been developed using methods such as regression, decision trees, and other statistical analyses to generate a credit score using limited amounts of structured data. However, in some cases, CSPs and CRSPs are increasingly turning to additional, unstructured, and semistructured data sources, including data sources such as open banking transactions (see, for example, PSD 2, the revised Payment Services Directive [European Commission 2015]) and data obtained from mobile phone use and other digital sources, in an effort to capture a richer and more granular view of an applicant's creditworthiness and improve the accuracy of models (Sidiqqi 2005). In markets that use credit scoring models based on traditional data sets, a potential borrower is required to have enough historical credit information available to be considered scorable. In the absence of this information, a credit score cannot be generated, and a potentially creditworthy borrower is often unable to gain access to lending in acceptable conditions.

By combining innovative algorithms and new data, a much more detailed assessment of the creditworthiness of consumers and businesses is possible. In essence, the world is changing and new data sources are being created. However, challenges remain as the models and important variables developed with techniques such as machine learning on new data sources may be difficult to interpret and may also require additional testing.

In addition to facilitating a potentially more precise, segmented assessment of creditworthiness, the use of innovative algorithms in credit scoring may help enable greater access to credit. In summary, using alternative data sources and applying innovative algorithms to assess creditworthiness, CSPs may be able to arrive at credit decisions that previously would not have been possible.

Credit Scoring Definitions

Credit Scoring

Credit scoring is a statistical method used to predict the probability that a loan applicant, existing borrower, or counterparty will default or become delinquent. It provides an estimate of the probability of default or delinquency, which is widely used for consumer lending, credit cards, and mortgage lending (Kenton 2019).

Credit scores provide an indication of creditworthiness. They are typically a numerical expression that indicates how likely a consumer or business is to make credit repayments regularly and in full, including any additional charges, such as interest and fees. Scores can be scaled to any numerical range; generally, the higher the credit score of the borrower, the lower the risk of nonpayment of credit. CSPs may use credit scoring in risk-based pricing in which the terms of a loan, including the interest rate offered to borrowers, are based on the credit risk of the borrower.

The main advantage of a credit score is that it is a quick, consistent and effective way for CSPs to be able to decide on an applicant's eligibility for a loan or contractual payment scheme (box 1.1). It also impacts relative product pricing and profitability of the CSP.

Credit Ratings

The assessment of the creditworthiness of businesses, large corporations, and sovereign governments is generally done by a credit rating. Credit ratings may apply to companies, sovereigns, subsovereigns, and those entities' securities, as well as asset-backed securities.

A good credit rating of a counterparty indicates a high possibility of repayment of debt obligations in full. A poor credit rating suggests that the counterparty has had trouble repaying debt obligations in the past and might face those challenges again in the future (Kagan 2019).

Credit ratings typically apply to companies (usually larger corporations) and governments, whereas credit scores typically apply to individuals and to micro, small, and medium enterprises (MSMEs). Credit ratings are assigned either by credit rating agencies or, internally, by CSPs. For instance, Standard & Poor's has a credit rating scale ranging from AAA (excellent) to C and D (a rating below BBB- is considered a speculative grade, which means the counterparty is more likely to default on financial obligations).

Credit ratings are important because they determine a counterparty's access to credit, shape the terms of conditions of credit facilities such as interest rates charged by CSPs, and influence potential investor decisions. Business credit scoring is largely used for business loans and trade credit assessment. Table 1.1 provides a summary of the main differences between credit scores and credit ratings.

Box 1.1: What is a Credit Scorecard?

A credit scorecard consists of a group of characteristics, statistically determined to be predictive in separating good and bad loans or counterparties. Examples of scorecard characteristics include demographic data, credit account performance, bank transaction data, real estate data, and so forth. Each attribute is assigned points based on statistical analyses (For example, "Time at job" is a characteristic and "5-10 years" is an attribute). The predictive strength of the characteristics, correlation between characteristics, and operational factors affect the assignment of scorecard points. An individual's credit score is then, a sum of the scores of the characteristics presented in the scorecard.

Source: Siddiqi, 2017.

Table 1.1: Differences between Credit Scores and Credit Ratings

	Credit Scoring	Credit Rating
Subject	Individuals, MSMEs, medium enterprises, corporations	SMEs, medium enterprises, corporations, sovereigns, securities, asset-backed securities
Data used	Demographics, past credit behavior, company and financial statement information, alternative data	Financial statements, industry, business risks, management information
Methodology	Statistical	Expert judgment or hybrid
Producers	CRSPs and CSPs, including credit managers	Credit rating agencies and CSPs using the internal rating-based approach, if approved by the regulator
Users	Credit providers; credit managers; relevant public authorities, including Central Banks and so on	Investors; companies wishing to assess counterparties for trade credit; relevant public authorities, including Central Banks and so on
Depth and breadth	Low-value, high-volume retail lending	High-value, low-volume wholesale lending
Scale	Any numerical range	AAA to D or 1 to 30

Credit Scoring Use Cases

Credit scores and credit ratings are used during all stages of the credit life cycle. Examples are as follows:

- Application scores that are based on a borrower's application information influence the CSP's decision for approval or rejection of the loan request and pricing
- Behavioral scores that are based on known information about a borrower's historical behavior in different aspects of the credit life cycle
- Collection scores that depict the likelihood of the loan or the borrower moving further into delinquency based on various criteria including the borrower's previous performance
- Early warning scores that alert the CSP of an event (internal or external) that may affect the credit risk of the borrower
- Fraud detection scores that are based on the validation of information and behavior and help the CSP to be alerted of potentially fraudulent activities

Regulatory Developments

Regulatory developments, including the Basel II Accord and IFRS (International Financial Reporting Standards) 9, and model risk management have placed additional focus on the credit risk modeling processes within CSPs.

Regulatory Capital Requirements

In 1988, the Basel Committee on Banking Supervision published the Basel I Capital Accord (BCBS 2003). The main objectives of Basel I were to promote the soundness and stability of the banking system and to adopt a standard approach across banks in different countries. Although it was initially intended to apply only to the internationally active banks in the G-10 (Group of Ten) countries, it was finally adopted by more than 120 countries and recognized as a global standard. However, the shortcomings of Basel I became increasingly obvious over time.

Principal among them were that the risk weightings were insufficiently granular to capture the cross-sectional distribution of risk. Regulatory capital ratios were increasingly becoming less meaningful as measures of capital adequacy, particularly for large, complex financial institutions. Moreover, the simplicity of Basel I encouraged rapid developments of various types of products that reduce regulatory capital.

The Basel II objective was to put in place a regulatory capital framework that is sensitive to the level of risk taken on by banks (box 1.2). The Basel II Accord has contributed significantly to CSPs' development of their own credit scoring (Sidiqqi 2017). CSPs that are required to comply with the Basel II Accord's internal rating-based approaches are required to generate their own estimates of probability of default (as well as loss given default and the exposure at default for the Advanced approach) for on- and off-balance sheet exposures and demonstrate their competency to regulators. In addition, CSPs that were not required to comply with the Basel II Accord considered the use of in-house credit scoring methods to improve consistency and efficiency, bring down costs, and reduce losses. Through investments in data warehouses and analytical capability, credit scoring offers a quick and proven way to use data to reduce losses while increasing profitability.

International Financial Reporting Standards 9

The International Accounting Standards Board (IASB) issued the final version of IFRS 9, Financial Instruments, in July 2014 (IASB 2014). The standard, referred to as IFRS 9 (with its counterpart in the United States: Current Expected Credit Loss), supersedes IAS (International Accounting Standards) 39, Financial Instruments: Recognition and Measurement, for financial entities, allocating provisions in accordance with the expected credit loss approach, instead of an incurred loss approach. The new accounting standard uses forward-looking default estimates for expected credit loss calculations.

It is designed to provide a principle-based classification and measurement approach for financial assets; a single, forward-looking impairment model; and a better link between accounting and risk management for hedge accounting (box 1.3).

Under IFRS 9, a forward-looking approach is required for the computation of probability of default (PD), loss given default (LGD), and exposure at default (EAD). The 12-month and lifetime expected credit loss is derived from these three parameters, typically with a macroeconomic overlay providing the expected forward-looking element. A point-in-time default estimate is a key ingredient of the IFRS 9 expected credit loss calculation.

Box 1.2: Basel II Summary[18] (BCBS, 2003)

Basel II Is Supported By Three Pillars

Pillar 1 defines the rules for calculating the minimum capital requirements for credit, operational and market risks. The minimum capital requirements are composed of three fundamental elements: a definition of regulatory capital, risk weighted assets and the minimum ratio of capital to risk weighted assets.

Pillar 2 provides guidance on the supervisory review process which enables supervisors to take early actions to prevent capital from falling below the minimum requirements for supporting the risk characteristics of a bank and requires supervisors to take rapid remedial action if capital is not maintained or restored.

Pillar 3 recognizes that market discipline has the potential to reinforce minimum capital standards (Pillar 1) and the supervisory review process (Pillar 2), and so promote safety and soundness in banks and financial systems.

In addition to underwriting, regulatory capital calculations, and impairment, credit scores and credit ratings may also be used in a bank's stress testing and economic capital calculations.

Management of Risk Models

The regulatory scrutiny of the management of risk models has intensified around the globe. The requirements dictate that an effective model governance framework be used within regulated CSPs.

In April 2011, the Board of Governors of the Federal Reserve System and the Office of the Comptroller of the Currency (OCC) published SR 11-7, Supervisory Guidance on Model Risk Management (Federal Reserve System 2011). They define "model" as "a quantitative method, system, or approach that applies statistical, economic, financial, or mathematical theories, techniques, and assumptions to process input data into quantitative estimates." The guidance states that the increasingly heavy dependence on models in financial decision-making processes "invariably presents model risk, which is the potential for adverse consequences from decisions based on incorrect or misused model outputs and reports" and lays out the key principles for model risk management. The guidance broadened the scope of model risk management beyond model validation to the end-to-end model life cycle from development to implementation to ongoing usage. The guidance explicitly addressed the criticality of strong governance processes in the overall effectiveness of model risk management that include board and senior management oversight, policies and procedures, controls and compliance, and an appropriate incentive and organizational structure.

Furthermore, SR 11-7 highlighted the need to consider "risk both from individual models and in the aggregate." Aggregate model risk is affected by interaction and dependencies among models. It is particularly important for credit scoring models given their heavy use in all aspects of the credit life cycle and in many regulatory capital calculations and reporting contexts.

SR 11-7 expects institutions to align the sophistication of the governance process with that of the models. This approach elevated the need for increased focus on the governance of credit scoring models given its pace of innovation.

In 2017, the European Central Bank (ECB) also published strict guidelines, including the Targeted

Box 1.3: IFRS 9 Summary

IFRS 9 comprises the following three key parts:

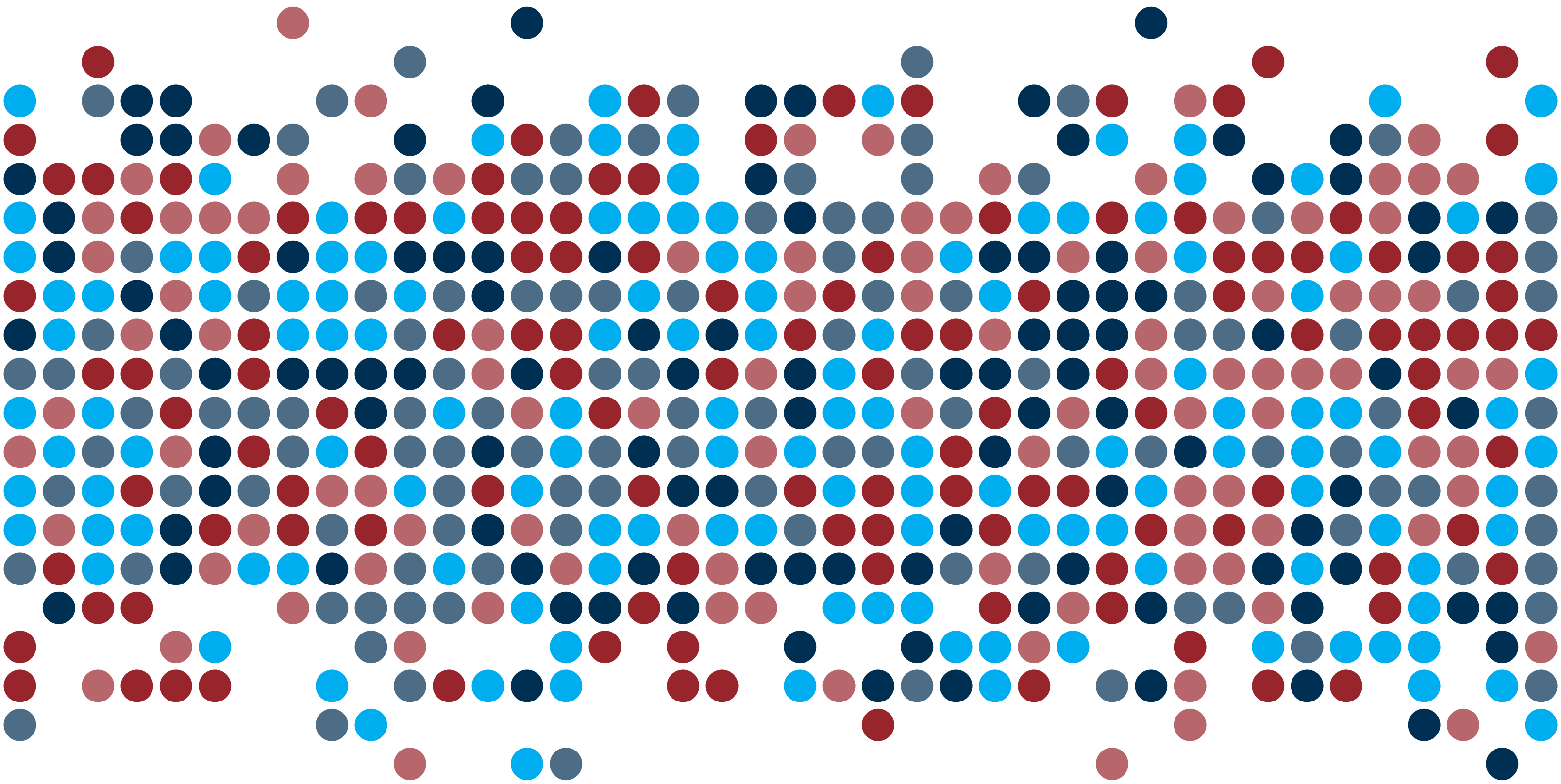
Part 1—Classification and measurement:
A new model for the classification and measurement of financial assets is introduced, based on a business model assessment and analysis of contractual cash flows (also known as the Solely Principle Payments and Interest [SPPI] test).

Part 2—Impairment:
It replaces the IAS 39 incurred loss model with an expected credit loss (ECL) approach for financial assets not measured at fair value through profit and loss (FVTPL).

Part 3—Hedge accounting:
General hedge accounting requirements create a closer link between risk management and hedge accounting. However, IFRS 9 allows a choice to continue IAS 39 hedge accounting because macro hedge accounting rules have not been finalized.

Source: IASB 2014.

Review of Internal Models (TRIM), for banks in the European Union (ECB 2017). TRIM requires institutions to have an effective model risk management framework that allows them to identify, understand, and manage model risk of all models. TRIM indicates that model risk should be treated like any other risk category. TRIM further emphasizes that the model validation process should include any contributing subsets or modules such as scorecards.



2. DATA

Introduction

Digitalization and the digital footprints left by consumers and businesses have caused a rapid growth in the data sources available for credit scoring, broadening the possibilities to generate insights beyond traditional data sources. Data have become a vital resource for organizations, entities, and governments.

It is anticipated that the use of alternative data may greatly increase the ability of CSPs to serve those that have difficulty accessing affordable credit within developing and developed economies (Owens and Wilhelm 2017). Such use is also considered a means for consumers and businesses to move from the informal sector to the formal sector (GPFI 2018).

Notwithstanding the benefits of using more data for credit scoring, the increased volume of data presents an increased number of challenges such as access to good quality data, cyber attacks, consumer data protection violations, and exploitation of vulnerabilities by aggressive marketing.

Role of Data in Credit Scoring

Since the establishment of CRSPs, data have been a pivotal enabler of the assessment of credit risk (Chappell et al. 2018). CSPs evaluate potential borrowers through an underwriting process that relies heavily on credit scores and credit ratings. In addition, data play an important role in the development, monitoring, and maintenance of credit scoring models.

As a result of digitalization, more data have become available, allowing CSPs and CRSPs to develop models with higher predictive power and deeper insights and to offer new products to sectors of society that were previously excluded from access to affordable credit.

Types of Data Used for Credit Scoring

The data used for credit scoring come from diverse and multidimensional sources (table 2.1). For credit scoring, traditionally, credit data are used, including amount of loan, type of loan, maturity of loan, guarantees and collateral value, historical payment performance such as default information and payments in arrears, amounts owed, length of credit history, new credit, and types of credit. These data are factored into a credit score as indicators of willingness and ability to pay (Márquez 2008).

These conventional data sets are typically the property of the CSPs.

This guideline differentiates between data from traditional and alternative sources. It further differentiates between structured, unstructured, and semistructured data sources (Trujillo et al. 2015).

The Global Partnership for Financial Inclusion defines alternative data as a generic term that designates the massive volume of data that is generated by the increasing use of digital tools and information systems (GPFI 2018). Alternative sources may include real-time transactional data, mobile and other devices data, social media, utilities data, and data from applications. In addition, data such as psychometrics, biometrics, web browsing, news feeds, online ratings and blogs, images (such as analysis of satellite images), property

Table 2.1: Types of Data Used for Credit Scoring

Data category	Data type	Credit scoring application
Traditional	Bank transactional data	Records of late payments on current and past credit, current loan amounts and loan purpose, credit history
Traditional	Credit bureau checks	Number of credit inquiries
Traditional	Commercial data	Financial statements, number of working capital loans, and others
Alternative	Utilities data	Steady records of on-time payments as possible consideration as an indicator of creditworthiness
Alternative	Social media	Social media data with possible insights on consumer's lifestyle
Alternative	Mobile applications	Mobile payment systems with possible view on the consumer's behavior
Alternative	Online transactions	Granular transactional data with possible detailed insights on spending patterns
Alternative	Behavioral data	Psychometrics, form filling

data, and supplier or shipping data may also provide rich insights. These alternative sources are often referred to as "alternative data" (ICCR 2018).

Structured data are typically stored in traditional databases. For example, a structured database may record a company's daily operational transactions.

Unstructured data usually do not have a predefined order. Examples of unstructured data include free-form text, images, social media data, video, audio, and the like.

Semi-structured data does not conform to the form of structured data. Instead, they contain tags or markers.

The usefulness, objectiveness, and quality of unstructured data to improve credit scoring methods are not yet firmly proved (CGFS and FSB 2017). The lawful use of unstructured data holds potential for further analysis. Several regulatory bodies have set up sandbox environments to support data innovation, such as those in Australia, Singapore, and the United Kingdom and in Taiwan, China (FCA 2019).

Modern credit scoring systems can collate data from a wide variety of data sources in structured, unstructured, and semistructured form. New sources of data are sometimes used, including granular spending behavior, mobile data, geolocation data, and payment data from other sources such as utilities and, in some cases, social media data for companies (box 2.1).

Common types of alternative data used in credit scoring methods can come from granular transactional data, mobile data, social media data, and behavioral data.

Granular Transactional Data

For consumers and businesses, granular transactional data may include the usage behavior of a transactional

Table 2.1: Types of Data Used for Credit Scoring

Examples of factors are as follows:

- Payment history: A record of late payments on current and past credit accounts may have an adverse effect on an individual's score. Payments on time and in full may improve the score.
- Public records: Matters of public record such as bankruptcies, judgments, and collection items may impact the score.
- Amount owed and loan purpose: High levels of debt may impact the score. The purpose of the loan and the type of CSP may also be linked to creditworthiness.
- Length of credit history and length of time at address: Length of credit history and time at current address are associated with creditworthiness.
- New accounts: Opening multiple new credit accounts in a short period of time may impact the score.
- Credit bureau checks: Whenever a request for a credit report is made, the inquiry is recorded. Recent inquiries may impact the score.
- Social media data: Social media data may provide insights into a consumer's lifestyle, indicating credit worthiness.
- Mobile data: Mobile data may provide granular information and insights into consumer behavior.
- Utilities data: A steady record of payments may contribute to an individual's credit score.
- Commercial data: Financial statements, operational information, and working capital loans may indicate the creditworthiness of businesses.
- Macroeconomic data: A change in the macroeconomy (that is, a change in the unemployment rate or GDP of a region) may impact the credit scores of consumers and businesses in that region.

account (for example, the granular transactions of a credit card). They usually provide an organized view given their operational nature and information on past payment behavior (Siddiqi 2017). Other types of transactional data include real-time e-commerce data and data from accounting systems.

For SME and corporate entities, more granular transactional data have proved useful in a credit scoring context. Several CSPs have developed tools to process transactions in real time from operating accounts into detailed revenue and expense items, combined with analysis to generate, for example, simplified financial statements and affordability ratios. Transactional data may offer substantially richer and more up-to-date insights about company performance than annual accounts can offer (Barasch 2017), and the logic holds for an individual's creditworthiness.

Mobile Data

A substantial increase in smart phone use has given rise to a wide variety of structured and unstructured data that may be used to assess the behavioral patterns of mobile phone users. Mobile applications may collect the data, such as transport movements, geolocation, and transactional data. The data may allow mobile phone applications to perform the requisite credit checks that traditional CSPs may find challenging (Grab 2018). The data subjects may be unaware that their personal data are used for credit scoring.

Social Media Data

Some research studies have suggested that the number of posts and their frequency may lead to a better understanding of the lifestyle of consumers, their expenditures, and their willingness to repay debt (Blazquez and Domenech 2018).

Box 2.2: Use Case—Grab Financial and the use of Alternative Data

Grab Financial Services is a joint venture company between a Southeast Asia's on-demand transportation platform, Grab Inc. (Grab), and Credit Saison Co., Ltd. ("Credit Saison"), one of the largest consumer financing institutions in Japan.

The joint venture seeks to provide a reliable alternative to traditional credit scoring methods for the unbanked and underbanked majorities in Southeast Asia.

By analyzing behavioral and transactional data from the application platform, such as transport movements, geolocation, and payment transaction data, more data points are available to assess credit worthiness.

The financial platform provides both financial products and credit scoring services.

Source: Grab 2018.

Behavioral Data

Behavioral data track human actions and behavior such as psychometrics and form filling (box 2.2).

A further extension of the analysis of social media data is the ability to analyze the network and connections of a consumer. The network and activity between connections have been cited to provide useful insights in the case where the applicant has no credit history (Rusli 2013). The quality and generic nature of social media data (obtained by web scraping, for example) raise concerns about data privacy and potential for fraud because the data have not been obtained directly from the consumer.

Utilities Data

Another useful source in credit scoring is the analysis of records of payment history of utility bills. This practice is based on the premise that historical payment behavior provides insights into the consumer's ability to make repayments.

Data Management

Innovations in computer technology and the demand for data drive continuous improvements in collecting, preparing, storing, analyzing, and distributing data. When the data are cleaned and transformed, combined with other sources, and kept historically, it can become very powerful items for analysis. The advancements in current data processing and computing technologies have resulted in a drastic decrease in costs of storage and processing, enabling more efficient means of collecting, managing, and analyzing extremely large data sets.

Data may be generated from systems and interactions between humans and systems for operational purposes. Although new data are generated for numerous reasons, the way they are generated and stored has important ethical and legal implications. For instance, data from a financial transaction cannot be used for the same purposes as the personal data from a profile on a social media platform. Data in the public domain are historically considered nonproprietary.

The growing amount of data creates opportunities for third parties to provide data management services such as collecting, cleaning, and combining data. The additional layers of new organizations within the data value chain may pose challenges of who is responsible and accountable for the accuracy and quality of the data. It may become challenging to map the data used for the final decision back to its data source.

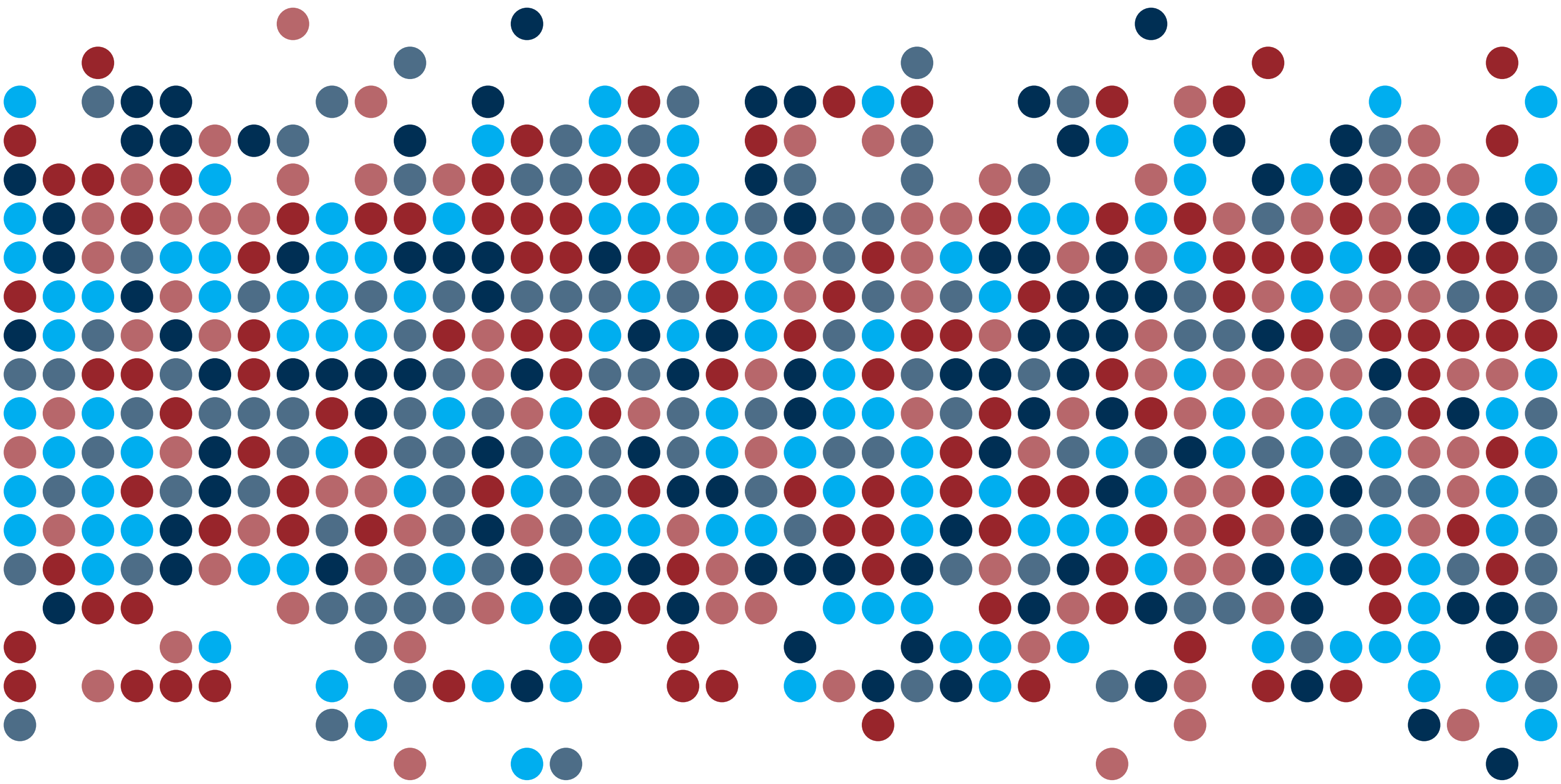
In some jurisdictions, regulatory requirements regarding the protection of personal data are in place (World Bank 2018; see box 2.3). CSPs holding personal data should have policies and robust capabilities to ensure they adhere to regulatory requirements. In addition, the enablement of data owners to share relevant proprietary data from services providers to CSPs may benefit risk frameworks.

Box 2.3: Consumer Rights Guidelines by the World Bank

Guidelines from the World Bank on consumer rights include mechanisms for consumers to do the following:

- Access their own data: Data subjects should be allowed to access their own data. This is an accepted practice in countries where data privacy laws are in place.
- Correct their own data: Consumers should be given options to correct their data if the data are inaccurate. This is an accepted practice in countries where data protection laws are in place. The use of alternative data from open sources highlights the greater need for identification of the data source, together with the party responsible for the accuracy of the data because that party could also be responsible for responding to and fulfilling consumer requests on data corrections.
- Cancel and/or erase data: In those circumstances where it is possible, the right to cancel (erase) data is linked to the right to the obsolescence of data and the usefulness of such data. For example, according to the European Union's General Data Protection Regulation, the grounds on which a data subject can exercise the right to be forgotten include situations where the consent to process is withdrawn by the data subject and there is no other legal processing basis. If data are processed on the basis of legitimate interests that are not overridden by the interests or fundamental rights and freedoms of the data subject, the right to object is possible for only very specific reasons (European Union 2016).
- Oppose the collection of their data: The right to oppose the collection of data may be exercised, for example, by the introduction of white lists for marketing purposes. However, there are certain types of data and circumstances for which the data subjects cannot object to the processing of such data (that is, credit repayment data for credit risk evaluation when such repayment is in default).
- Enable portability of their data: In those circumstances where it is possible, consumers should be able to obtain and reuse their personal data for their own purposes across different services. They should be allowed to move, copy, or transfer personal data easily from one platform to another in a safe and secure way, without affecting the usability.

Source: World Bank and CGAP 2018; World Bank 2016b; European Union 2016.



3. CREDIT SCORING METHODOLOGIES

Introduction

The methods used for credit scoring are evolving from traditional statistical techniques to innovative methods such as artificial intelligence, including machine learning such as random forests, gradient boosting, and deep neural networks.

Traditional Credit Scoring Methods

The most prominent techniques used to develop credit scorecards are statistical discrimination and classification methods. These include linear regression models, discriminant analysis, logit and probit models, and expert judgment-based models.

Linear Regression

Regression analysis is particularly useful in credit scoring because the statistical approach is easy to explain and predict risk parameters, such as the probability of default. In linear regression, the label (dependent variable or target outcome) is projected on a set of features (covariates or independent variables). Parameters that minimize the sum of squared residuals are chosen.

Discriminant Analysis

Discriminant analysis is a variation of regression analysis used for classification. The label is based on categorical data. The simplest variation is a label with two categories (for example, "default" versus "nondefault"). The original dichotomous linear discriminant analysis was developed by Sir Ronald Fisher in 1936 (Fisher 1936).

In default prediction, linear discriminant analysis was the first statistical method applied to systematically explain which firms entered bankruptcy, based on accounting ratios and other financial variables. Edward Altman's 1968 model is still a leading model in practical applications (Altman 1968).

The original Altman Z-score model, developed using data of publicly held manufacturers, was as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

where

X_1 = *working capital / total assets*

X_2 = *retained earnings / total assets*

X_3 = *earnings before interest and taxes / total assets*

X_4 = *market value of equity / book value of total liabilities*

X_5 = *sales / total assets*

Probit Analysis and Logistic Regression

For the dichotomous label in credit scoring, there have been several efforts to adapt linear regression methods to domains where the output is a probability value instead of any infinite real number. Many of such efforts focused on mapping the binary range to an infinite scale and then applying the linear regression on these transformed values.

In the probit model, an abbreviation for "probability unit," the inverse standard normal distribution of the probability is modeled as a linear combination of the features. The logit function uses the log of odds, which is an abbreviation for "logistic unit" following the analogy for probit. In the logit model, the log of the odds ratio of the label is modeled as a linear combination of the features.

The logit model is a popular model for estimating the probability of default, because it is easy to develop, validate, calibrate, and interpret. Rather than choosing parameters that minimize the sum of squared errors (as in ordinary regression), estimation in logistic regression chooses parameters that maximize the likelihood of observing the sample values (see appendix A for technical specification).

Judgment-Based Models

Multiple methods may be employed to derive expert judgment-based models. One such a method is called the analytic hierarchy process (AHP), which is a structured process for organizing and analyzing complex decisions. The AHP model is based on the principle that when a decision is required on a given matter, consideration is given to information and factors, which can be represented as an information hierarchy. The decision makers decompose their decision problem into a hierarchical structure of more easily comprehended subproblems, each of which can then be independently analyzed. The key element of the AHP is that human judgments, not only the underlying information, be used to perform the evaluations. Human judgment is particularly critical in evaluating exceptions and instances that do not have precedence or are significantly underrepresented in the data.

For example, Bana e Costa, Barroso, and Soares (2002) developed a qualitative credit scoring model for business loans based on concepts of the AHP.

Artificial Intelligence and Machine Learning in Credit Scoring

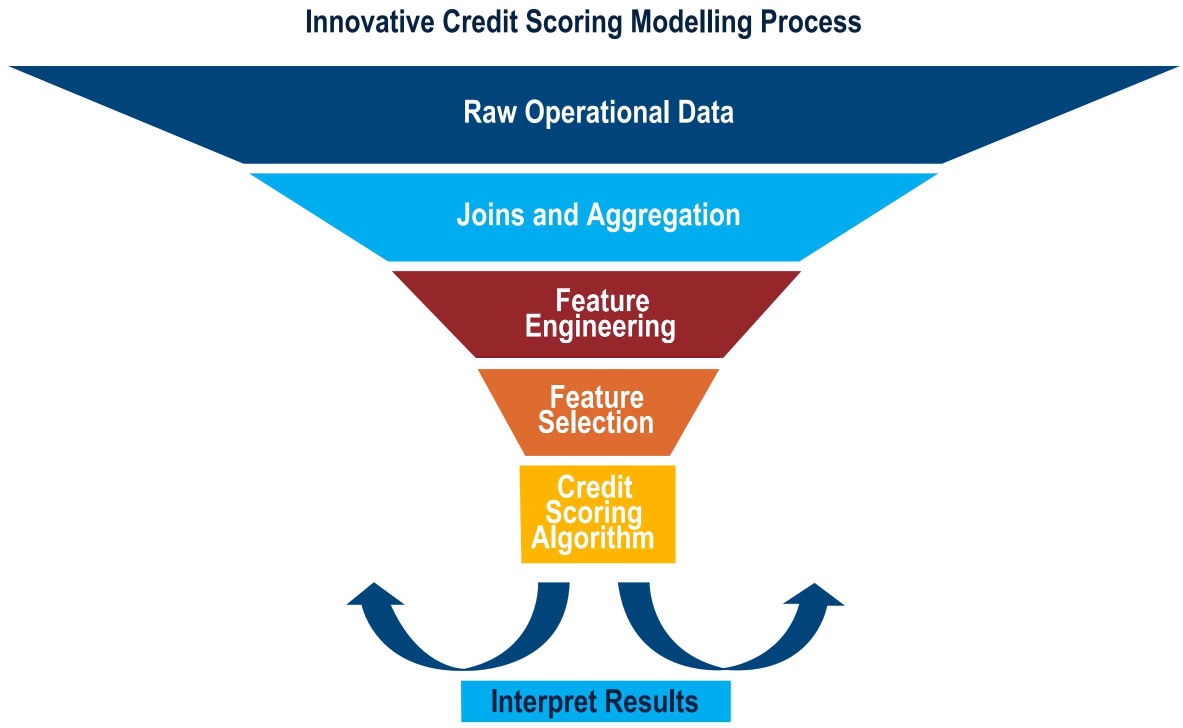
Artificial intelligence (AI) is the application of computational tools to address tasks traditionally requiring human sophistication (SAS 2019). AI enables machines to learn from experience, adjust to new inputs, and perform human-like tasks (FSB 2017). Most AI examples that are popular today—from self-driving machines to superhuman doctors—rely heavily on deep learning and natural language processing. These techniques leverage the ability of computers to perform tasks, such as computer vision and chatbots, by learning from experience.

Today's evolving AI is made possible by rapid development in foundational technologies such as computing power, data, and innovative algorithms. Using these technologies, computers can be trained to accomplish specific tasks by processing and recognizing patterns in the data, while the data may be of different types and from different sources.

AI is a broad field, and machine learning is a subcategory. Machine learning is defined as a method of designing a sequence of actions to solve a problem, known as an algorithm, which optimize automatically through experience with limited human intervention (SAS 2019). These techniques can be used to find complex patterns in large amounts of data from increasingly diverse and innovative sources (SAS 2019).

Deep learning is a form of machine learning that uses algorithms that work in layers inspired by the structure and function of the human brain (SAS 2019). Deep learning algorithms can be used for supervised, unsupervised, or reinforcement learning. Recently, deep learning has led to remarkable results in fields such as image recognition and natural language processing. For example, deep learning may be used to classify images, recognize speech, detect objects, and describe content. Voice recognition systems are powered, in part, by deep learning.

Box 3.1: Machine Learning for Credit Scoring



At a high level, the application of machine learning algorithms for credit scoring involves the following high-level process that can be split further into multiple subphases:

- Access raw data.
- Combine, join, and aggregate input data.
- Engineer features, either manually using expert input or using automated approaches.
- Select useful features.
- Apply the machine learning algorithm to the training data set.
- Interpret and assess results (see figure 3.1).
- Some techniques include a feedback loop where the algorithm learns from experience.

Innovative credit scoring methods include supervised, unsupervised and semi-supervised learning techniques.

Supervised Learning Techniques

In supervised learning, the algorithm is developed using data that contain a label (dependent variable or event) and independent features (variables). The algorithm then predicts future or unknown values of the label of interest, using features (independent variables). For instance, a data set of counterparties may contain labels on some data points identifying those that are in default and those that are not in default. The algorithm will learn a general rule of classification that it will use to predict the labels for other observations in the data set.

Some of the supervised techniques include regression, decision trees, random forests, gradient boosting and deep neural networks.

Decision trees

Decision trees are typically schematic, tree-shaped diagrams used to show a statistical probability. Classification and regression trees (CART) are one of the most well-established supervised learning techniques. CART works by repeatedly finding the best feature to split the data into subsets. The partition improves the isolation of the label with each split.

Decision trees can be used for either classification, for example, to determine the category of an observation (that is, default or nondefault), or for prediction, for example, to estimate a numeric value (that is, the loss given default).

Random forests

Random forests are a combination of tree predictors such that each tree depends on a sample (or subset) of the model development data (or training data) selected at random (Breiman 2001). Working with multiple different subdata sets can help reduce the risk of overfitting. Random forests or random decision forests are ensemble methods for regression and classification problems based on constructing a multitude of decision trees and outputting the class that may be either the mode of the classes (classification) or the mean prediction (regression) of the individual trees (see appendix A for technical specification).

Gradient boosting

Gradient boosting is an ensemble method for regression and classification problems. Gradient boosting uses regression trees for prediction purposes and builds the model iteratively by fitting a model on the residuals. It generalizes by allowing optimization of an objective function.

Deep neural networks

Instead of organizing data to run through predefined equations, deep neural networks train the algorithm to learn on its own by recognizing patterns using many layers of processing.

Deep neural networks, also referred to as deep-learning networks, are neural networks with additional hidden layers. Each layer of nodes trains on a set of features based on the previous layer's output. Hence, progression through each layer results in increasingly complex layers of features that are aggregated, recombined information learned from the previous layer.

This characteristic makes deep-learning networks able to identify highly complex nonlinear patterns with large volumes of data and dimensions (Press 2017). On the flip side, deep neural networks are also prone to overfitting (see appendix A for technical specification). Overfitting may be reduced by validating a new model on an out-of-sample data set.

Other popular techniques include support vector machines (see appendix A for technical specification).

Unsupervised Learning Techniques

Unsupervised learning refers to methods where the data provided to the algorithm do not contain labels (events). The algorithm is required to detect patterns in the data by identifying clusters of observations that demonstrate similar underlying characteristics, for example. In other words, these algorithms serve to explore the properties of the data examined, rather than to predict new or unknown data. Unsupervised techniques include clustering, K-means clustering, and hierarchical clustering.

Clustering

Clustering is the process of obtaining natural groups from the data. These are groups and not classes, because, unlike classification, instead of analyzing data labeled with a class, clustering analyzes the data to generate this label. The data are grouped on the basis of the principle of maximizing the similarity between the elements of a group by minimizing the similarity between different groups. That is, groups are formed such that the objects of the same group are very similar to each other and, at the same time, they are very different from the objects of another group.

Clustering algorithms are descriptive rather than predictive. For example, a clustering algorithm may be used to look for a borrower that has characteristics similar to a borrower that is difficult to assess. If the algorithm finds an appropriate cluster for the borrower, the average default assessment of the cluster may be used as an estimate of the default assessment of the borrower.

This report distinguishes between two types of clustering methods: K-means and hierarchical clustering.

K-means clustering

K-means clustering aims to partition a set of observations into K clusters, resulting in the partitioning of the data into groups. It starts by placing K central positions (centroids) in random locations in the multidimensional (Euclidian) space. It then uses the Euclidean distance between data points and centroids to assign each data point to the cluster that is closest. The process is iterative (see appendix A for the technical specification).

Hierarchical clustering

Hierarchical clustering starts by assigning all data points as their own cluster. Based on the Euclidian distance, it then combines the two nearest data points and merges them together to form a new cluster. The process continues until convergence.

Other Techniques Related to Credit Scoring Methods

Automated Feature Engineering

The success of machine learning models highly depends on the success of feature engineering. Feature engineering is the process of transforming the input data set into features to better understand the underlying structures in the data and improve model accuracy.

The process may be highly iterative: multiple sets of features may be created and evaluated in several phases. Thousands or even millions of feature candidates may be generated; thus, there is a need to intelligently select relevant candidates and to avoid overfitting in subsequent model development.

Owing to its manual nature, the traditional approach to feature engineering tends to be tedious, time consuming, and error prone. The emergence of automated feature engineering seeks to address these shortcomings and allow analysts to spend their time more efficiently on other aspects of the modelling process (Koehrsen 2018).

One such example is the deep feature synthesis algorithm, which automatically performs feature engineering on relational and multitable data (Kanter and Veeramachaneni 2015). The algorithm captures features by stacking multiple primitives. Feature primitives are basic mathematical operators that can be applied to raw variables as aggregations and transformations. An example of a transformation is the ratio of two raw variables such as debt and income. Primitives are used to form new features by applying them across data sets or stacking them to create more complex features.

Reinforcement Learning

Reinforcement learning is an emerging method that falls between supervised and unsupervised learning. It has been applied in credit processes such as collections.

Reinforcement learning allows the machine to learn behavior based on feedback from the environment. This behavior can be learned once or adapted as time goes by (Champandard n.d.).

The goal is to train an algorithm that considers the environment, takes actions, and receives feedback from the environment in terms of rewards (the feedback mechanism) to learn which optimal actions to take. The ideal behavior maximizes the reward. Reinforcement learning is popular in robotics and game theory.

This automated learning scheme implies that there is little need for human intervention.

Natural Language Processing

Natural language processing (NLP) is the ability of machines to analyze, understand, and generate human language, including speech. It is a branch of artificial intelligence that helps computers understand, interpret, and manipulate human language. NLP draws from many disciplines, including computer science and computational linguistics. For text, NLP often uses semantics, concept identification, and sentiment analysis. The next stage of NLP is natural language interaction, which allows humans to communicate with machines using normal, everyday language to perform tasks (SAS 2019). NLP capabilities can be extended to natural language understanding, which is how a machine tries to understand the meaning of spoken or written language. This field goes beyond just the structural understanding of language into the ability of a system to interpret intent, resolve context and word ambiguity, and even generate well-formed language on its own.

Blockchain for Decentralized Credit Scoring

A blockchain is a distributed ledger in which any computer that is part of a network can participate. For data to be updated on the blockchain, they require verification from multiple sources.

A main benefit of the blockchain network is that it lacks centralized points of vulnerability for hackers to exploit, reducing cybersecurity risks. Blockchain security methods use encryption technologies. This feature enables blockchain technology to provide a much higher level of security in storing information ("What Is a Blockchain?" 2018). Several financial technology providers have leveraged this process to provide users a more secured means to retrieve their credit score, as well as share credit history with CSPs.

Decentralized credit scoring takes thousands of features of a user's credibility from multiple data sources, while credit scores are calculated via decentralized credit scoring algorithms. The features may consider data from social media to online shopping history to create a universal digital identity and a comprehensive credibility profile owned by the individual ("Colendi Technical Paper" n.d.; box 3.1). However, blockchain is not yet widely adopted for credit scoring. A significant issue with blockchain is that there is yet no significant scalability and that the costs per transaction tend to rise steeply.

Understanding and Interpreting Credit Scoring Models

Introduction

One major concern raised by regulatory and industry bodies (Monetary Authority of Singapore n.d.; Foy 2018) is the ability for humans to interpret, understand, explain, and justify the decisions made by credit scoring methods using large numbers of variables, particularly using new, innovative approaches.

Box 3.1: Use Case—Colendi

The Colendi platform is as follows:

- Colendi is a decentralized microcredit platform that uses machine-learning algorithms to generate a credit score and identity check based on alternative data sources while ensuring safety and privacy. Colendi can help provide services to the underbanked and unbanked.
- Users authorize the Colendi protocol to read data related to their smartphones, social media, purchases, and more than 1,000 personal data points to be used in credit scoring machine-learning models.
- The credit scoring machine-learning models are designed to analyze the data through integrated blockchain nodes without changing or retaining the data, ensuring that any data that are available to the application are not moved to any servers or revealed to any parties.

Source: "Colendi Technical Paper" n.d.

The European Banking Authority (EBA) and other regulatory bodies highlighted the need for further research to improve the interpretability of the models to mitigate risks such as bias and discrimination (European Commission 2018a).

Interpretability can also be defined as tackling the challenge of asserting a causal connection between input data to models and the way that input data impact model output and decisions (Tan 2018).

Interpretability of Model Inputs

Understanding of the input data is important to strengthen trust and to ensure that personal data are lawfully used and the risk of amplifying bias in historical data is addressed. Interpretability of the model inputs can be increased by documenting input data, with sufficient tracking of permission where applicable; utilizing exploratory data analysis; and ensuring the selection of meaningful features is justified and proper governance of feature selection is in place. Highly engineered features are useful to improve model accuracy; however, they may not be interpretable when used in the models.

Interpretability of Modelling Logic

Traditional approaches like regression and decision tree algorithms are interpretable and explainable when used with few features. The models typically use interpretable transformations and show intuitive relationships, which help users understand the models.

Linear models are particularly easy to interpret because the relationship between the features and the label is modelled in a linear function. Linear models can also be used to effectively capture nonlinear relationships (for example, exponential relationships) by transforming raw variables. The linearity of the learned relationship makes the interpretation easy and straightforward.

Decision trees are also easy to interpret; by starting from the root node, one can trace the classification logic through the rule sets. The leaf nodes inform the label.

Deep neural networks, random forests, and gradient boosting machines are regularly considered as opaque or black box models (FSB 2017). These algorithms use many features and complex transformations, making it challenging to interpret the relationship between the feature and the target.

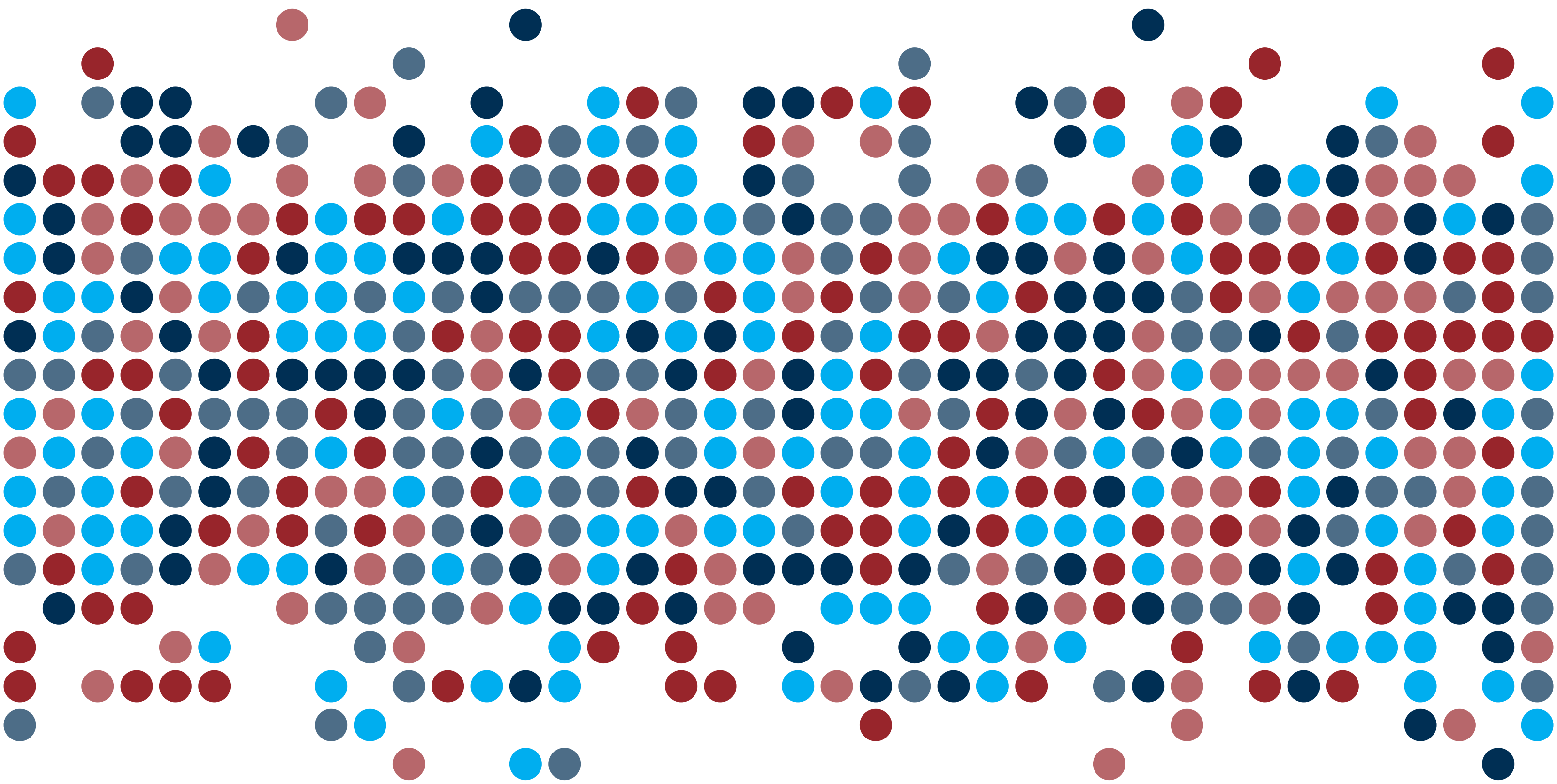
Interpretability of Postmodelling Results

Some research studies (FSB 2017) consider the interpretation of the model predictions to help inspect the dynamics between input features and output predictions. Postmodelling results analysis may be necessary in cases where, for example, the machine learning model is opaque.

Postmodelling interpretability tests can help in the understanding of the most important features of a model: how those features affect the predictions, how each feature contributes to the prediction, and how sensitive the model is to certain features.

Model-agnostic techniques include partial dependence (PD) plots, individual conditional expectation (ICE) plots, and local interpretable model-agnostic explanations (LIME) (Champandard n.d.). See appendix B for specification.

Model-specific techniques include variable importance output from random forest, for example.



4. OPPORTUNITIES, RISKS & CHALLENGES

Introduction

Credit scoring has immense potential to assist the economic growth of the world economy and can be a valuable tool for improving financial inclusion and efficiency. Industries, regulators, and governments working together to harness the benefits is critical to the further development of the positive aspects of its innovation, while at the same time managing its risks and challenges. Ensuring that everyone can help in building an enhanced society and can participate in the benefits of innovative technologies is also important (NSTC 2016).

As highlighted by the Financial Stability Board (FSB) (2017), there are potential benefits and risks for financial stability as the technologies are adopted in the coming years and as more data become available. The more efficient processing of information (for example, in credit decisions) may contribute to a more efficient financial system.

Opportunities

Financial Access and Inclusion

According to the World Bank, up to two billion adults globally do not have a basic bank account while more than 200 million formal and informal MSMEs in emerging economies do not have adequate financing owing to a lack of collateral and credit history (Press 2017). Furthermore, three billion people are unable to obtain a credit card, and 91 percent of residents in developing nations face challenges receiving debt financing from traditional financial institutions. The absence of a credit history leaves millions of potentially creditworthy individuals without access to credit (Press 2017). Allowing for a wider variety of relevant information about the credit applicant to be collected and considered may increase the chances for a higher number of consumers or businesses to be assessed, thereby also increasing their chances to gain access to credit.

For example, consumers with short credit histories may not satisfy a CSP's traditional lending requirements, However, the same consumers may potentially be offered a loan from a CSP that uses alternative data and innovative algorithms (Carroll and Rehmani 2017).

As another example, financial technology providers may use alternative data by asking potential borrowers to go through a process, such as downloading an application to their phones, to allow the providers access to their mobile phone data. The types of data collected and used by technology providers can vary. They may include phone usage patterns, such as duration of calls, number of contacts, and types of applications being downloaded.

Automation of Processes

The use of innovative credit scoring models may help reduce the cost of making credit decisions and performing credit monitoring and lower the operating costs for CSPs. Innovative credit scoring methods allow large amounts of data to be analyzed very quickly. As a result, they could yield credit scoring policies that handle a broader range of credit inputs, lowering the cost of assessing credit risk for consumers and increasing the number of consumers for whom CSPs can measure credit risk. Examples include the automation of repetitive tasks in the risk assessment process and the assessment of real-time bill payments, such as the timely payment of mobile phone and other utility bills, in combination with other data. In summary, digitalization may greatly improve the automation, efficiency, and speed of credit decisions.

Enhanced Consumer Experience

By widening the variety of analytical capabilities and increasing the size of data sets that are analyzed, innovative credit scoring models provide opportunity to CSPs to achieve deeper insights, provide better personalized customer experience, and develop new financial products.

Better Predictive Models, More Accurate Decisions

A more accurate credit score provides a more complete picture of borrowers (Foy 2018; box 4.1). The use of innovative algorithms may improve the quality of credit risk assessments (Proudman 2018). CSPs would be in a better position to offer competitive interest rates, which is currently a commonly cited challenge. Owing to improved accuracy in credit risk models compared to traditional credit scoring, existing borrowers could then benefit from fairer interest rates. In addition, higher accuracy in predictive models can also be achieved by innovative algorithms that run in real time and use data sources that are collected on a more regular or real-time basis. For example, online transaction data and mobile application data may provide a more accurate and up-to-date view of credit risk.

Risks

Fairness

Algorithms that search through alternative data sources may detect personal data with legal and ethical restrictions, for example, discriminatory factors such as race, gender, or religion (World Bank and CGAP 2018; box 4.2). In addition, a combination of a consumer's geolocation data and other preferences may inadvertently approximate ethnicity (World Bank 2018). This report recommends that the fairness of credit scoring methods be assessed within the context of an ethical framework that upholds fundamental human rights and ethical principles and incorporates a CSP's values and codes of conduct.

Box 4.1: Use Case: Nova Credit

Nova Credit

Nova Credit is a cross-border CRSP that aims to solve the problem of credit access for immigrants in the United States. This is done primarily through integrations with credit databases internationally, allowing CSPs global access through a single API (application programming interface).

The company provides a service to expatriots and immigrants from Australia, Canada, India, Mexico, and the United Kingdom to make available their previous credit history when applying for selected products in the United States.

Avenues for Disputes

Nova Credit has a process in place for consumers to dispute the accuracy of the information in their Nova Credit Reports. Customers can initiate a dispute by submitting a dispute request form, which would be processed and investigated within 30 days unless applicable law permits more time. Nova Credit encourages customers to dispute inaccurate, incomplete, outdated, or unverifiable information as soon as possible because the negative information may indicate fraudulent activity or lead to a lower credit score.

Box 4.2: Discrimination and Biases

Research conducted in 2015 by the White House and the Federal Trade Commission indicated that the use of big data may result in discriminatory pricing. This is because consumers tend to be associated with their network of acquaintances, relatives, and ethnicity. As a result, only certain communities (in particular, African American communities) may be offered products at higher price. Research conducted in 2016 by the Federal Trade Commission also highlighted the concern that big data analytics could affect low income, underserved populations, and protected groups (especially in relation to credit and employment opportunities).

Other commentators have noted that, although there are arguments that algorithms can eliminate human biases, an algorithm is only as good as the data it works with. The selection of key attributes used in algorithms is also relevant because search engines' algorithms may learn to prioritize characteristics associated with a group of individuals (for example, minorities and women) more frequently than other characteristics not necessarily associated with those groups. Therefore, it might be useful to understand how meaningful the correlations found by the analytics tools based on big data are.

Source: World Bank 2018.

Interpretability

The use of complex algorithms could result in a lack of transparency. The opaqueness of innovative algorithms may raise concerns. When innovative algorithms are used to assign credit scores to make credit decisions, providing consumers, auditors, and supervisors with an explanation of a credit score and resulting credit decision if challenged is generally more difficult.

The lack of interpretability, or auditability, of innovative algorithms has the potential to contribute to macro-level risk if not appropriately supervised by regulators. Many of the models that result from the use of innovative algorithms are difficult to interpret. In addition, the lack of interpretability will make determining any potential cascading effects difficult owing to the interconnectedness of systems. Algorithms developed in a period of low volatility may not suggest optimal actions in a significant economic downturn or in a financial crisis.

Accountability

Many innovative algorithms in financial services may reside outside the regulatory perimeter or CSPs using the algorithms may not be familiar with applicable laws and regulations. Where financial institutions rely on third-party providers of innovative algorithms for critical functions, these service providers may not be subject to supervision and oversight.

With the increase in data usage and the longer data value chains, determining who is accountable and responsible for the data accuracy and quality may be challenging.

As noted by the FSB 2017, the scalability of new technologies may give rise to increased third-party dependencies. Large technology firms are increasingly offering innovative algorithms, while CSPs may use similar third-party data providers given their reputation, size, and scale. The FSB mentioned that the competition challenges may result in financial stability risks if a firm were to face a major disruption (FSB 2017).

Data Privacy

The public has expressed an increasing concern about privacy and the need for more transparency about how data are collected, processed, and used from online digital and/or mobile data footprints and other forms of information (World Bank and CGAP 2018).

Box 4.3: Equifax 2017 Case

In 2017, Equifax experienced a cybersecurity incident following a criminal attack on its systems that involved the theft of certain personally identifiable information of U.S., Canadian, and U.K. consumers. Criminals exploited a U.S. website application vulnerability to gain unauthorized access to the company's network.

In March 2017, the U.S. Department of Homeland Security distributed a notice concerning the software vulnerability. Equifax discovered unusual network activity in late-July 2017 and, upon discovery, promptly investigated the activity. Once the activity was identified as potential unauthorized access, Equifax acted to stop the intrusion and engaged a leading, independent cybersecurity firm to conduct a forensic investigation to determine the scope of the unauthorized access, including the specific information impacted. A forensic investigation indicated that the unauthorized access of information occurred from mid-May through July 2017. No evidence was found that the company's core consumer, employment and income, or commercial reporting databases were accessed. Equifax continues to cooperate with law enforcement in connection with the criminal investigation into the actors responsible for the 2017 cybersecurity incident.

Immediately following the announcement of the 2017 cybersecurity incident, the company devoted substantial resources to notifying people of the incident and providing free services to assist people in monitoring their credit and identity information.

Equifax also undertook significant steps to enhance its data security infrastructure. The company also enhanced its disclosure controls and procedures and related protocols to specifically provide that cyber incidents are promptly escalated and investigated and reported to senior management and, where appropriate, to the Board of Directors. Equifax also engaged an independent outside consulting firm to help with both strategic remediation activities and a review of its cybersecurity framework, controls framework, and management and employees' roles and responsibilities.

Digital credit decision processes may operate in a nontransparent manner, using opaque methods and data sets. The credit decision process may be unable to provide details on how the personal data are gathered and used. The lack of transparency exposes potential borrowers to losing track of how their personal data are used to make decisions.

Most developing countries have very limited legislation in place to govern the use of personal data for decision processes. The Global Partnership for Financial Inclusion (GPFI) highlights limitations with consent clauses, including the fact that consent is typically tied to standard adhesion contracts allowing limited choice for consumers to negotiate their way (World Bank and CGAP 2018). However, if these risks are properly mitigated, then it unlocks massive potential for underserved communities.

Data Security

Using alternative data for credit scoring would require CSPs to store and access extremely large volumes of personal data of consumers and businesses. Hence, there is a need for enhanced security measures owing to the increased risk of identity theft with the use of new data sources and increased connected relationships.

A recent case of large-scale identity theft occurred in 2017. During the Equifax data breach (box 4.3), consumer personally identifiable information was compromised (Equifax 2019).

Unintended Consequences

A well-intentioned algorithm may inadvertently make biased decisions that may discriminate against protected groups of consumers. For example, if there are limitations in the data used for model development, selection bias may occur. If there are limitations in the methodology used to develop the models, then statistical bias may occur. If historical data are used where social bias was prominent, the algorithm may enforce and amplify the social bias (for example, penalizing along racial lines).

Another classic challenge with innovative algorithms is their tendency to overfit the data. This occurs when the algorithm has adjusted too closely to a specific training data set to the extent that it is unable to make accurate predictions on new data. An overfitted machine learning model does not generalize well and performs poorly on data on which it was not trained.

Challenges

Potential for Discrimination

The use of alternative data sources and innovative algorithms may unintentionally discriminate against vulnerable pockets of society (European Commission 2018a). Specifically, consumer advocacy groups point out that machine learning algorithms can yield combinations of borrower information that approximate protected variables that may be prohibited by fair lending laws.

Consumer Protection

Consumer protection encompasses the rights of consumers, fair trade, competition and accurate market information, and protection of the vulnerable in society against discrimination. CSPs should integrate data privacy into the design process of credit scoring methods. Privacy Impact Assessments will ensure that personal data are not unlawfully used (European Union 2016). Data controllers should put in place mechanisms for consumers to access and correct information. The lawful collection and processing of personal data is required. Security risks should be properly monitored and managed. The need for further protection of the privacy and security of personal data may pose infrastructure challenges.

Model Governance

Beyond the staff handling applications for credit decisions, key functions such as risk management, and internal audit, should be adequately prepared for controlling and managing the use of models within credit scoring methods. Scarcity of resources with regard to the required skills and knowledge may pose challenges to CSPs and supervisors. In discussions with regulators while compiling this report, representatives noted the challenges posed by conducting audits effectively, including sufficient in-house skills to understand and supervise the models.

Disparity in the Maturity across Markets

The maturity of technological advances, infrastructure, and perspectives on the legal and ethical use of credit scoring methods vary across markets, cultures, and regions. In emerging markets, CSPs may still be operating on the basis of the credit officer's individual judgement. The talent and data infrastructure required to execute the more innovative approaches may still be very limited in many markets. The varying views toward data privacy across countries is another factor that has led to differing rates of innovation in credit scoring and the development of new financial services products.

Currently, CSPs find it challenging to operate globally, meaning that when borrowers move to a new country, they are required to rebuild their credit scores from scratch because their scores often cannot transfer cross-border (box 4.4). For identity verification, applying for credit requires consumers to expose all their personal information, putting individuals at increased risk of experiencing identity theft (Leimgruber, Meier, and Backus 2018).

Globalization and the cross-border establishment of large financial institutions constitute a major challenge to the regulation of financial activities. Owing to the growing interdependence in international financial markets, financial difficulties experienced in one country can easily impact other countries. A lack of a common set of international guiding principles creates a challenge for CSPs to innovate across their businesses on an international scale.

5. REGULATORY OVERSIGHT

Introduction

Credit scoring methods are subject to regulations related to data protection, fairness, capital requirements, accounting standards, and model governance. Because there is no global, standardized framework in place today (FSB 2017), this section focuses on some of the key regulatory frameworks applicable to credit scoring methods. To ensure the responsible use of innovative credit scoring algorithms, current regulations may need to be updated or extended to also apply to innovative methods. In addition, the capacity and technical proficiency of regulatory bodies need to be encouraged and expanded for the effective review and challenge. In addition, it is recommended that, especially in emerging markets, the level of financial literacy and numeracy of consumers be considered by the conduct of the CSPs.

Summary of Key Regulatory Frameworks

A summary of key regulations related to credit scoring models includes those of the FSB, Basel Committee on Banking Supervision (BCBS), European Banking Authority (EBA), European Data Protection Board (EDPB), European Securities and Markets Authority (ESMA), and the U.S. Federal Reserve System (the FED).

Financial Stability Board

In the wake of the 2008 global financial crisis, the G-20 (Group of Twenty) finance ministers and central bank governors established the FSB (FSB 2017) in April 2009 (table 5.1).

Table 5.1: Overview of Financial Stability Board

Regulation	Key Objectives	Who Oversees	Who Does It Apply to
FSB: Use of AI/ML in financial stability[a]	The FSB develops a framework that defines the scope of fintech activities and identifies the potential benefits and risks to financial stability.	The FSB is accountable to the G-20 to prepare reports on issues of global importance.	The FSB is responsible for overseeing the policy-development functions of all the international standard-setting bodies, such as the BCBS, IASB, and IOSCO), to improve overall institutional accountability.

Basel Committee on Banking Supervision

The BCBS is an international committee formed to develop standards for banking regulation (table 5.2). It was formed in 1974 by central bankers from the G-10 countries. The BCBS is headquartered in the offices of the Bank for International Settlements (BIS) in Basel, Switzerland.

The main objectives of the first Basel accord were to promote the soundness and stability of the banking system and adopt a standard approach across banks in different countries. Although it was initially intended to be only for the international active banks in the G-10 countries, it was finally adopted by over 120 countries and recognized as a global standard. However, a shortcoming of the Basel I framework was that regulatory capital ratios were less meaningful as measures of true capital adequacy, particularly for large and complex financial institutions.

The Basel II goals were set by means of three mutually supporting pillars:

- Pillar 1 defines the rules for calculating the minimum capital requirements for credit, operational, and market risks. The minimum capital requirements are composed of three fundamental elements: a definition of regulatory capital, risk-weighted assets, and the minimum ratio of capital to risk-weighted assets.
- Pillar 2 provides guidance on the supervisory review process that enables supervisors to take early actions to prevent capital from falling below the minimum requirements for supporting the risk characteristics of a bank and requires supervisors to take rapid remedial action if capital is not maintained or restored.
- Pillar 3 recognizes that market discipline has the potential to reinforce minimum capital standards (Pillar 1) and the supervisory review process (Pillar 2), and thereby promote safety and soundness in banks and financial systems.

European Banking Authority

The EBA is a regulatory body that works to maintain financial stability in the European Union's (EU) banking industry. The EBA was established in 2010 by the European Parliament and replaced the Committee of European Banking Supervisors (CEBS).

The EBA produces guidelines on information and communications technology (ICT) risk management and mitigation requirements in the EU financial sector.

European Data Protection Board

The EDPB is an EU body in charge of the application of the GDPR (table 5.3). It was

Table 5.2: Overview of Basel Committee on Banking Supervision

Regulation	Key Objectives	Who Oversees	Who Does It Apply to
Basel guidelines	The objective of the Basel guidelines is to reduce the unwarranted variability in capital requirements stemming from differences in model development and calibration practices.	BCBS supervises banks and ensures that they follow the rules set by the committee.	The guidelines are tasked with developing regulatory technical standards and making rules for financial firms in the EU internal market such as lending institutions, investment firms, and credit institutions.

a. FSB (2017).

established in 2018. The EDPB consists of the head of each Data Protection Authority in each EU Member State and of the European Data Protection Supervisor (EDPS) or his/her representatives.

European Securities and Markets Authority

ESMA is an independent EU Authority that contributes to safeguarding the stability of the EU's financial system by enhancing the protection of investors and promoting stable and orderly financial markets (ESMA 2019; table 5.4).

U.S. Federal Reserve System

The FED ensures that CSPs make credit available equally to creditworthy customers and are prohibited from discrimination (table 5.5).

The Federal Reserve Board (FRB) ensures that CSPs use credit scoring appropriately in the evaluation of consumers' credit risk. The FRB has three roles in connection with credit scoring. Regulation B prohibits discrimination against credit applicants on any prohibited basis, such as race, national origin, age, or gender. Regulation B also addresses the use of prohibited biases in credit scoring.

Table 5.3: Overview of European Data Protection Board

Regulation	Key Objectives	Who Oversees	Who Does It Apply to
General Data Protection Regulation[a]	The GDPR applies to personal data, meaning any information relating to an identifiable person who can be directly or indirectly identified in particular by reference to an identifier.	The DPAs assist the EDPB. The EDPB helps ensure that the data protection law is applied consistently across the EU and works to ensure effective cooperation among DPAs. The EDPB issues guidelines on the interpretation of core concepts of the GDPR and can also be called to rule by binding decisions on disputes.	The GDPR applies to all companies that deal with data of EU citizens, so it is a critical regulation for corporate compliance officers at banks, insurers, and other financial companies.

a. World Bank and CGAP 2018.

Table 5.4: Overview of the European Securities and Markets Authority

Regulation	Key Objectives	Who Oversees	Who Does It Apply to
Credit Rating Agency Regulation	ESMA carries out policy work in the area of Credit Rating Agencies in its role as the single supervisor of Credit Rating Agencies within the European Union.	European Securities and Markets Authority (ESMA) has direct supervisory power.	These guidelines apply to Credit Rating Agencies (CRAs) registered in accordance with the Regulation (EC) No 1060/2009 of the European Parliament and of the Council on credit ratings agencies (as last amended by Regulation (EU) No 462/2013 – CRA Regulation).

Table 5.5: Overview of the U.S. Federal Reserve System

Regulation	Key Objectives	Who Oversees	Who Does It Apply to
FED Regulation B	CSPs are prohibited from discriminating on the basis of age, gender, ethnicity, nationality, or marital status.	Regulation B is regulated and enforced by the Consumer Financial Protection Bureau (CFPB)	Banks, financial institutions, lenders, and leasing companies are required to comply with Regulation B when extending credit to individual borrowers.
Equal Opportunity Credit Acta	Ensure that financial institutions and firms that deal with credit extension make credit equally available to all creditworthy customers.	ECOA is regulated and enforced by the CFPB.	Banks, financial institutions, lenders, and leasing companies are required to comply with the ECOA when extending credit to individual borrowers.

a. Federal Reserve System 2006.

In its role as a supervisor of financial institutions, the FRB conducts fair lending examinations to ensure that CSPs are using credit scoring models that comply with the Equal Credit Opportunity Act (ECOA) and other applicable fair lending laws and takes enforcement action if it finds violations. The FRB also conducts safety and soundness examinations to ensure that financial institutions use credit scoring models in a sound manner.

Finally, as research institutions, the FRB and Federal Reserve Banks study significant trends in credit markets, such as the use of credit scores and credit scoring models; publish their research; and encourage research by other parties.

Equal Credit Opportunity (Regulation B)

The ECOA of 1974, which is implemented by the FRB's Regulation B, applies to all CSPs. The statute requires financial institutions and other firms engaged in the extension of credit to "make credit equally available to all creditworthy customers without regard to sex or marital status."

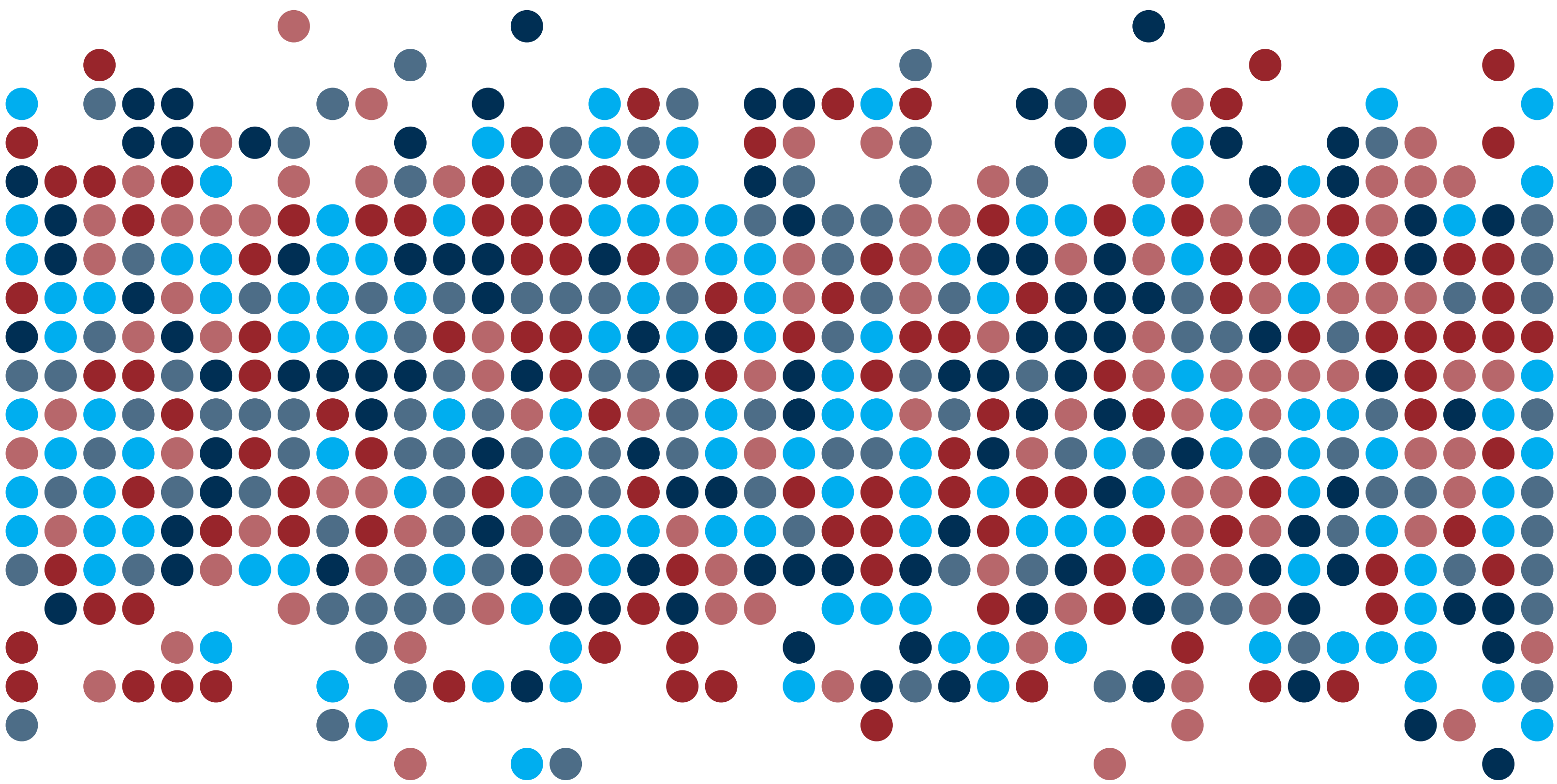
With regard to credit transactions, a creditor cannot discriminate on the basis of the following:

- An applicant's race, marital status, nationality, gender, age, or religion
- An applicant whose income is derived from a public assistance program
- An applicant who, in good faith, exercised his or her rights under the Consumer Credit Protection Act

Regulation B mandates that lenders provide an oral or written notice of rejection to failed applicants within 30 days of receiving their completed application. The notice must explain why the applicant was rejected, or give instructions for how the applicant can request this information.

6. TRANSPARENCY AND DISCLOSURE

The role of the regulator is to ensure safety, soundness, and stability of the financial system and to facilitate effective competition in markets. CSPs may operate internationally. It is therefore recommended that policy frameworks for supervision be agreed upon globally and have strong coordination with public authorities responsible for consumer protection, data protection, and cybersecurity. Some regulatory bodies have reported concerns about possible different levels of protection depending on whether or not the service is provided by a traditional bank or a new challenger player (EBA 2019). In addition, some regulatory bodies have recognized the need to collaborate with industry and better understand the downside risks of new innovations in the form of regulatory sandboxes (in Australia, Singapore [Monetary Authority of Singapore], and the United Kingdom and in Taiwan, China). A principle-based supervisory approach may apply, which may be judgment based and with priority given to those risks that pose the greatest risk to financial stability. This report does not recommend the replacement of any existing regulatory framework, but rather encourages a human-centric approach and the extension and updating of existing regulatory frameworks to also encompass innovative credit scoring methods. For example, the regulations that govern risk models may need to be extended to innovative algorithms used for credit scoring. Within the context of the management of models for credit scoring, CSPs should be able to quantify and explain any cascading risks associated with the use of credit scoring methods. It is also recommended that the data used within the models be justifiable.



7.
CONCLUSION

Credit scoring has immense potential to assist the economic growth of the world economy as well as being a valuable tool for improving financial inclusion and efficiency. It is critical that industries, governments, and regulators work together to harness the benefits, further developing the positive aspects of innovation, while at the same time managing its risks and challenges. Keeping the human at the center of the use of innovative credit scoring methods will help foster trust and build consumer confidence.

The opportunities of innovation in credit scoring include the following:

- Greater financial access and inclusion
- Automation of processes
- Improved accuracy of models
- Enhanced consumer experience

The risks of innovation in credit scoring includes the following:

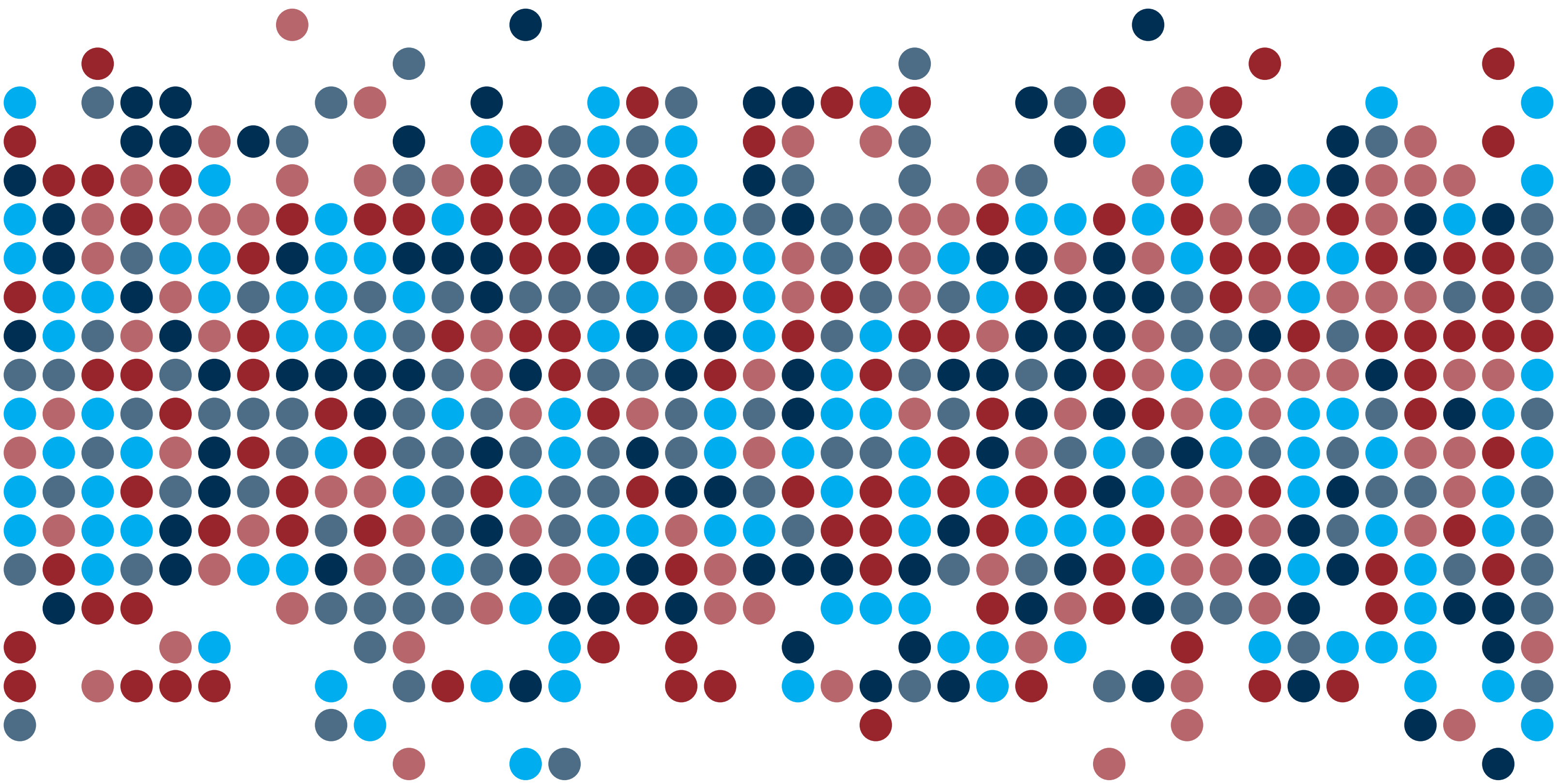
- Fairness
- Interpretability
- Accountability
- Data privacy and security
- Unintended consequences

Humans solve problems, not machines. Machines can surface the information needed to solve problems and then be programmed to address that problem in an automated way—based on the human solution provided for the problem.

Mary Beth Ainsworth, AI and Language Analytics Strategist, SAS

Trust is a prerequisite for CSPs in designing, developing, deploying, and using credit scoring methods. With innovative methods, several challenges require attention, including the potential for discrimination, the protection of consumer rights, the governance of models, and the disparity in maturity across markets.

The technologies supporting innovative credit scoring methods are still evolving, and it may therefore be necessary that the legal and ethical frameworks that are required to govern these should also evolve and mature over time. The seven policy recommendations listed in section 1 of the guideline provide guidance on the direction of the evolution and are designed to strengthen regulatory oversight roles and promote transparency.



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Appendix A.
CREDIT SCORING METHODOLOGIES

Generalised Additive Models

The generalized additive model for a binary classification is as follows:

$g(P) = \alpha + \beta' X$

where

α is the intercept parameter

$\beta = (\beta 1 \ldots \beta_n)'$ is the vector of model parameters

$X = (x_1 \ldots x_n)$ is the vector of features

P is the probability of an event (i.e. default)

g is the link function

- Linear Regression: g is the identity link function $g(P) = P$
- Logistic Regression: g is the logit link function $g(P) = \mathrm{logit}(P)$
- Probit Regression: g is the probit link function $g(P) = \mathrm{probit}(P)$

Decision Trees

The decision tree method recursively partitions the feature space into a set of rectangles and then fits a simple model (for example, a constant) in each one.

The CART algorithm for binary decision trees is as follows (Hastie, Tibshirani, and Friedman 2017):

- The starting region is the entire feature space.
- Choose the best splitting feature j, and split points that partition the data into two resulting regions

$R^1(j, s) = \{X| X_j \leq s\}$ and $R_2(j, s) = \{X| X_j > s\}$

by minimizing the misclassification error.

For any choice j and s, the inner minimization is solved by

$c1 = \text{average } (y_i| x_i \varepsilon R1(j, s))$ and $c_2 = \text{average } (y_i| x_i \varepsilon R2(j, s))$

Repeat the splitting process for each of the resulting regions. The depth of the tree is a tuning parameter that determines the algorithm's complexity. The optimal tree size is adaptively chosen from the data.

Random Forests

The random forest is the process of generating uncorrelated trees over a collection of bootstrapped samples and averaging them. For each tree, the features are selected at random as candidates for splitting.

The random forest algorithm for regression and classification is as follows (Hastie, Tibshirani, and Friedman 2017):

Let B be the number of trees to be grown.

- For b=1 to B:
  - Draw a bootstrap sample Z of size N from the training data.
  - Grow a random-forest tree Tb using the bootstrapped data by recursively repeating the following steps for each terminal node of the tree, until the minimum node size nmin is reached:
    - Select m features at random from the total number of features.
    - Pick the best feature/split-point among the m.
    - Split the node into two subnodes.
- Output the ensemble of trees from 1 to B: {Tb}

To make a prediction at a new point x, either the average or the majority vote is used.

Gradient Boosting

Gradient boosting is the process of fitting an additive model in a forward stage-wise manner. In each stage, the model fm(x) is improved from the previous version fm-1(x) by inducing a tree T(x;Θ) whose prediction is as close as possible to the negative gradient of the loss function -∂L/∂fm-1(x).

The gradient boosting algorithm may be used for binary or regression classification (Hastie, Tibshirani, and Friedman 2017).

Support Vector Machines

Support vector machine (SVM) is the process of finding an optimal hyperplane that separates different classes of data.

SVM supports both linear and nonlinear separation scenarios. In the latter case, the procedure constructs the linear boundary in an enlarged and transformed version of the feature space using a basis expansion h(x) that can be translated back to a nonlinear boundary in the original space. This transformation requires the knowledge of the kernel function K, which computes the inner products of vectors in the input space x in the transformed space.

Deep Neural Networks

A deep neural network (DNN) is a neural network with many hidden layers. The classical type of DNN is a multilayer perceptron (MLP), also called a feed-forward neural network. The information flows forward in one direction without a feedback loop:

- Data ingested into the input layer flow through many hidden layers.
- In each hidden layer j, additional features are derived by transforming the information from the previous layer through an activation function a(j). This is called forward propagation. The activation function, for example a sigmoid (logistic) function:

  $a^{(j)}$= sigmoid ($z^{(j)}$= $1/(1+e^{-z(j)})$

where

  $z^j = \Theta^{(j-1)}a^{(j-1)}$

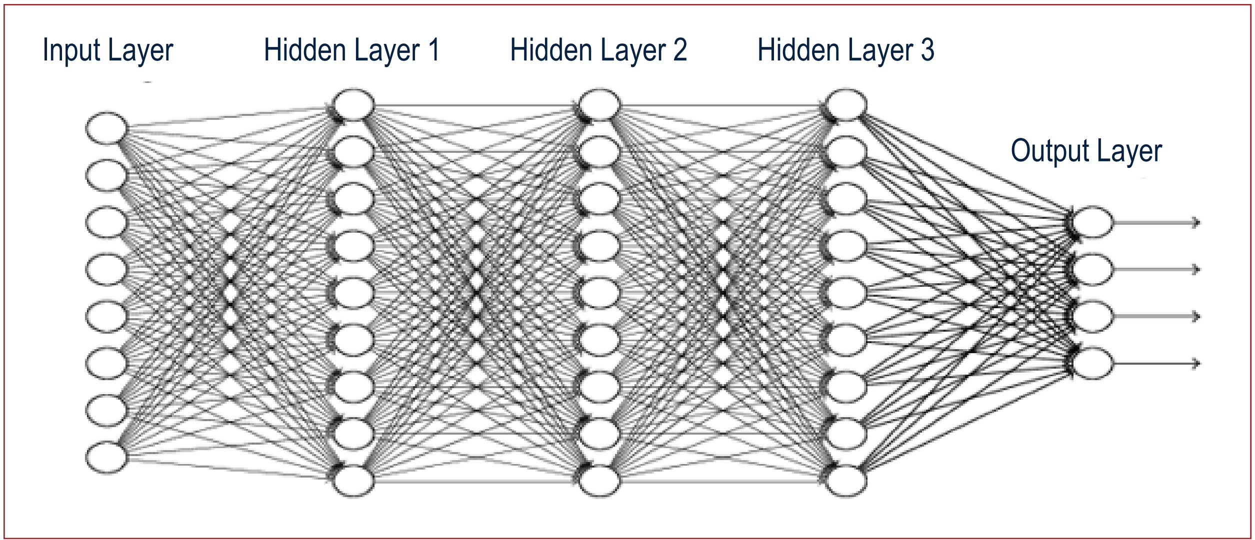
  Θ^{j-1} is the matrix of weight parameter.

- The prediction is simply the output from the output layer (figure A.1).

Fitting the neural network involves seeking the optimal weight parameter to minimize the cost function, thus making the model fit the training data. The generic approach to minimize the cost function is by gradient descent, which is called back-propagation.

For the back-propagation algorithm (Hastie, Tibshirani, and Friedman 2017), there are two passes in each iteration of the algorithm:

Figure A.1: Deep Neural Network



- In the forward pass, the weight parameters are fixed and the predicted values are computed through forward propagation.
- In the backward pass, the error terms are computed and back propagated. These are used to compute the partial derivatives of the cost function and update the weight parameters.

Other neural network architectures include, for example, convolutional neural networks and recurring neural networks.

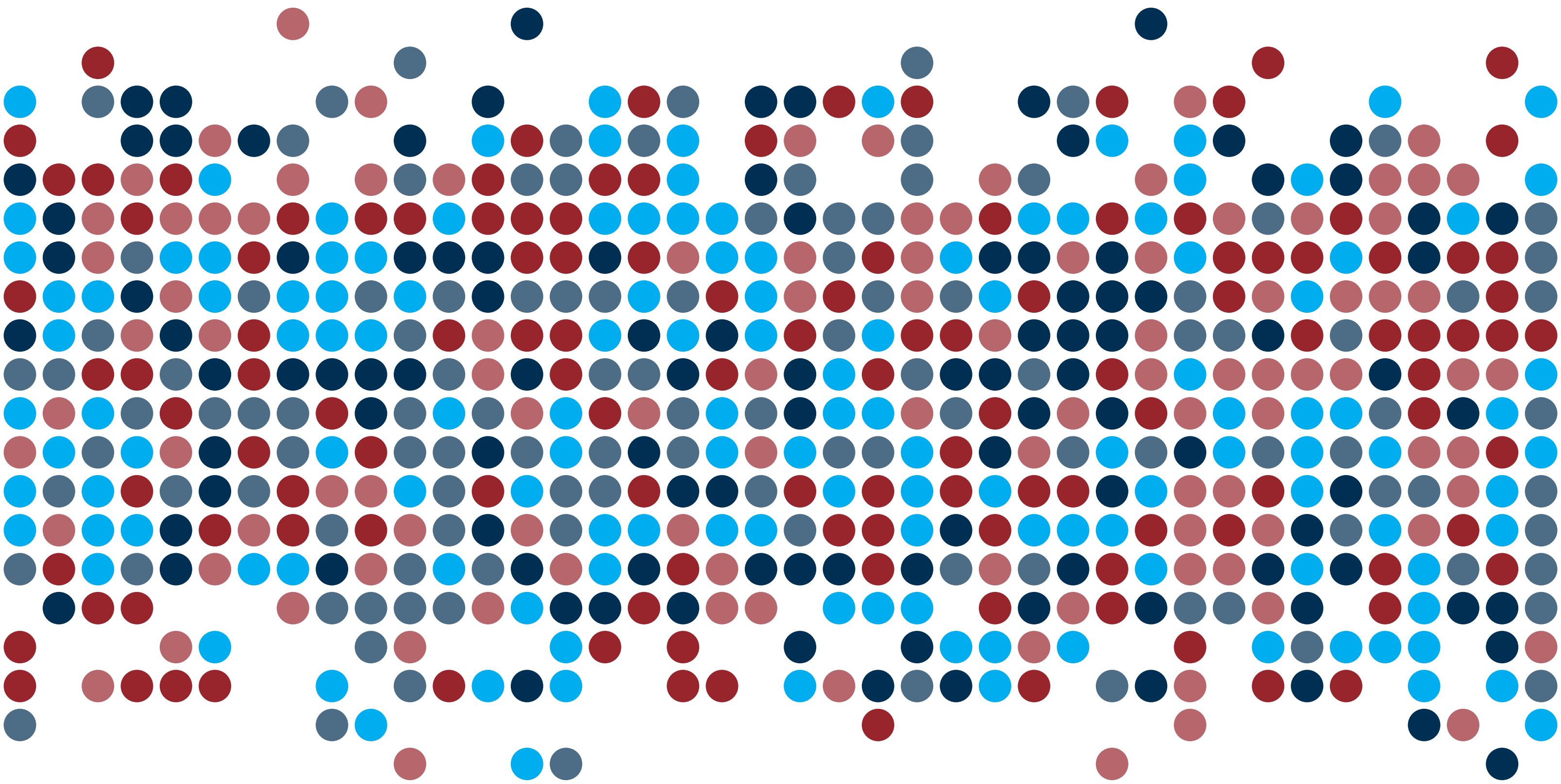
K-Means Clustering

K-means clustering is a method to find clusters and cluster-centers in a set of unlabeled data. The desired number of cluster-centers K is first selected, and the algorithm iteratively moves the centers to minimize the total cluster variance.

The total cluster variance can be defined as the sum of weighted Euclidean distances.

The K-means clustering algorithm is as follows (Hastie, Tibshirani, and Friedman 2017):

- For a given cluster assignment C, the total cluster variance is minimized with respect to {m1 … mK}, yielding the means of the currently assigned clusters.
- Given a current set of means {m1 … mK}, assign each observation to the closest (current) cluster mean. That is C(i) = argmin||xi − mk||2.
- Steps 1 and 2 are iterated until the assignments do not change.



APPENDIX B.
MODEL-AGNOSTIC INTERPRETABILITY TECHNIQUES

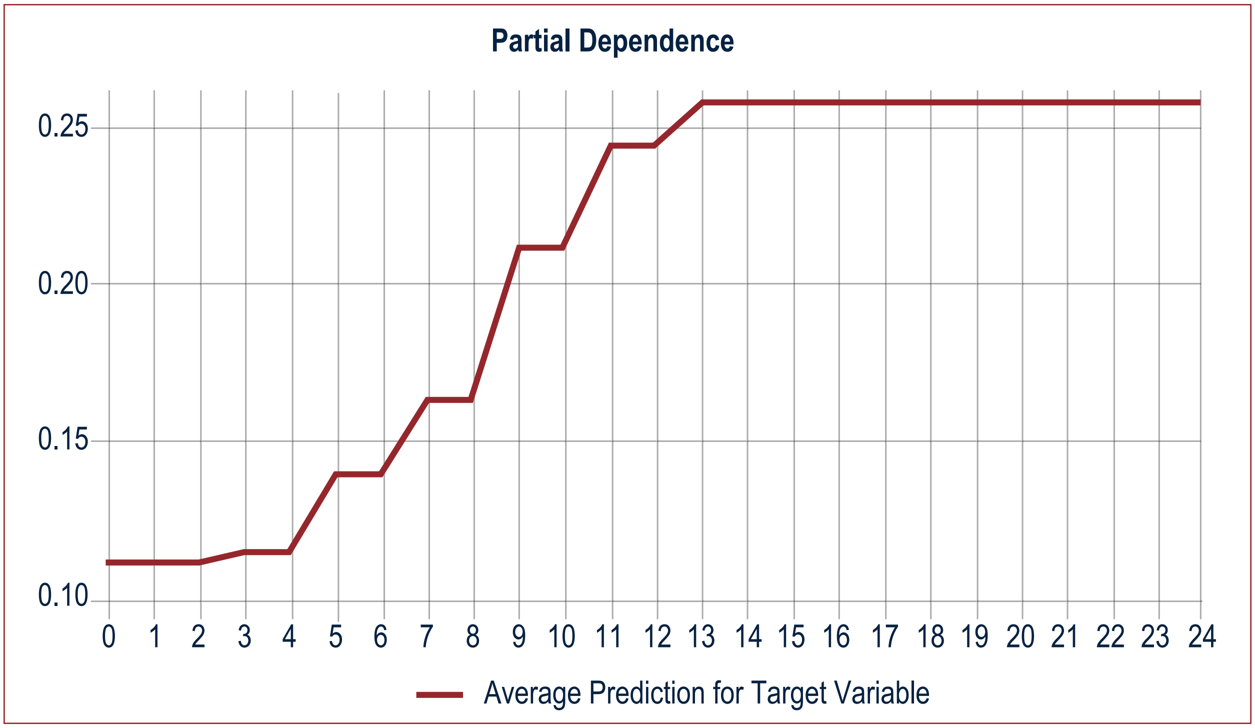
Partial Dependency Plots

A partial dependence (PD) depicts the functional relationship between a small number of input features and a model's prediction outcome (Kabul 2018). By plotting input features against the predictions of a model, the plots show how the predictions are related to the values of the input features of interest. The relationships may be linear, monotonic, or more complex (Kabul 2018). The PD plot works by building a model, averaging all other features except one chosen feature (the value of the input feature is depicted on the x-axis). The plot then measures the changes in response (figure B.1).

In the plot, if there are more variations for any given features, that means the value of that feature affects the model. In contrast, if the line is constant near zero, it shows that the feature has no effect on the model.

The PD plot for visualizing the average effect of a feature is a global method, because it does not focus on specific instances, but on an overall average.

Figure B.1: Example of a Partial Dependence Plot



Individual Conditional Expectation Plots

Individual conditional expectation (ICE) (Goldstein et al. 2014) plots draw one line per instance, enabling the drilling down to the level of individual observations. The plots disaggregate the PD function to reveal individual differences and interactions. It is recommended to plot one feature at a time (figure B.2).

An ICE plot visualizes the dependence of the predicted outcome on a feature for each instance separately.

Although PD plots can provide a high-level overview of the average relationship, an ICE plot would give more insight on interactions in the model.

Global Surrogate Models

Surrogate models are interpretable models (like a regression or a decision tree) that are learned on the output or predictions of a black box algorithm. They aim to replicate how the black box algorithm works.

One key benefit of surrogate models is that they grant a level of flexibility. Many types of interpretable models may be used as surrogate models to provide insight into complex algorithms. This approach may grant an added ease in implementation and explanation to an audience that is unfamiliar with data science concepts (Tan 2018).

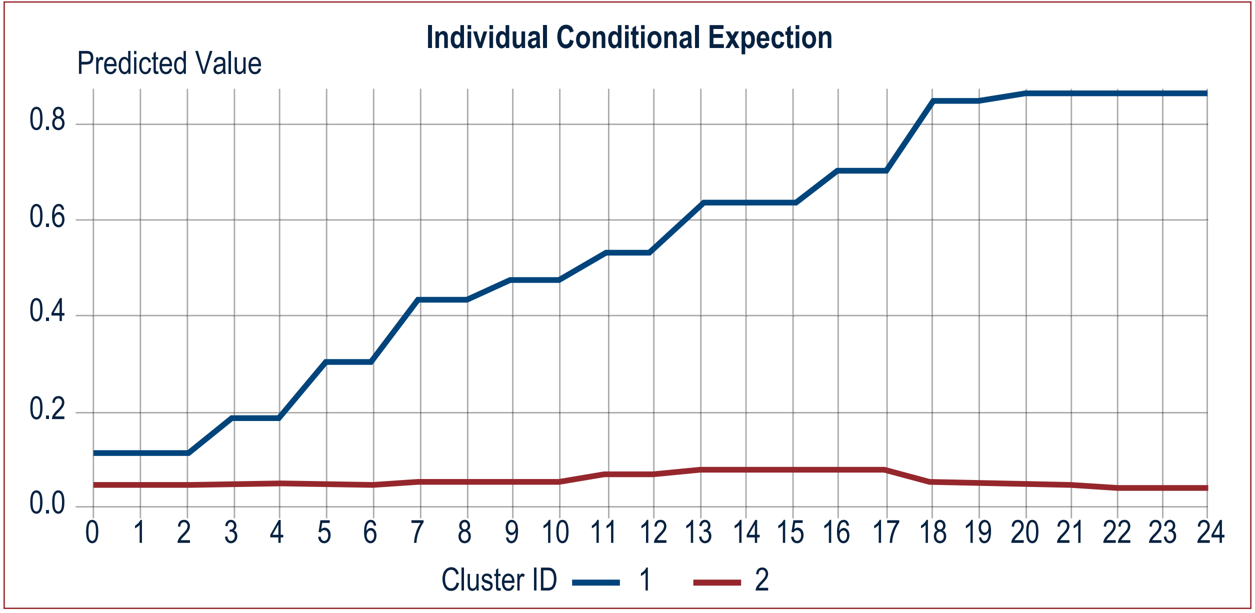
Local Interpretable Model-Agnostic Explanations

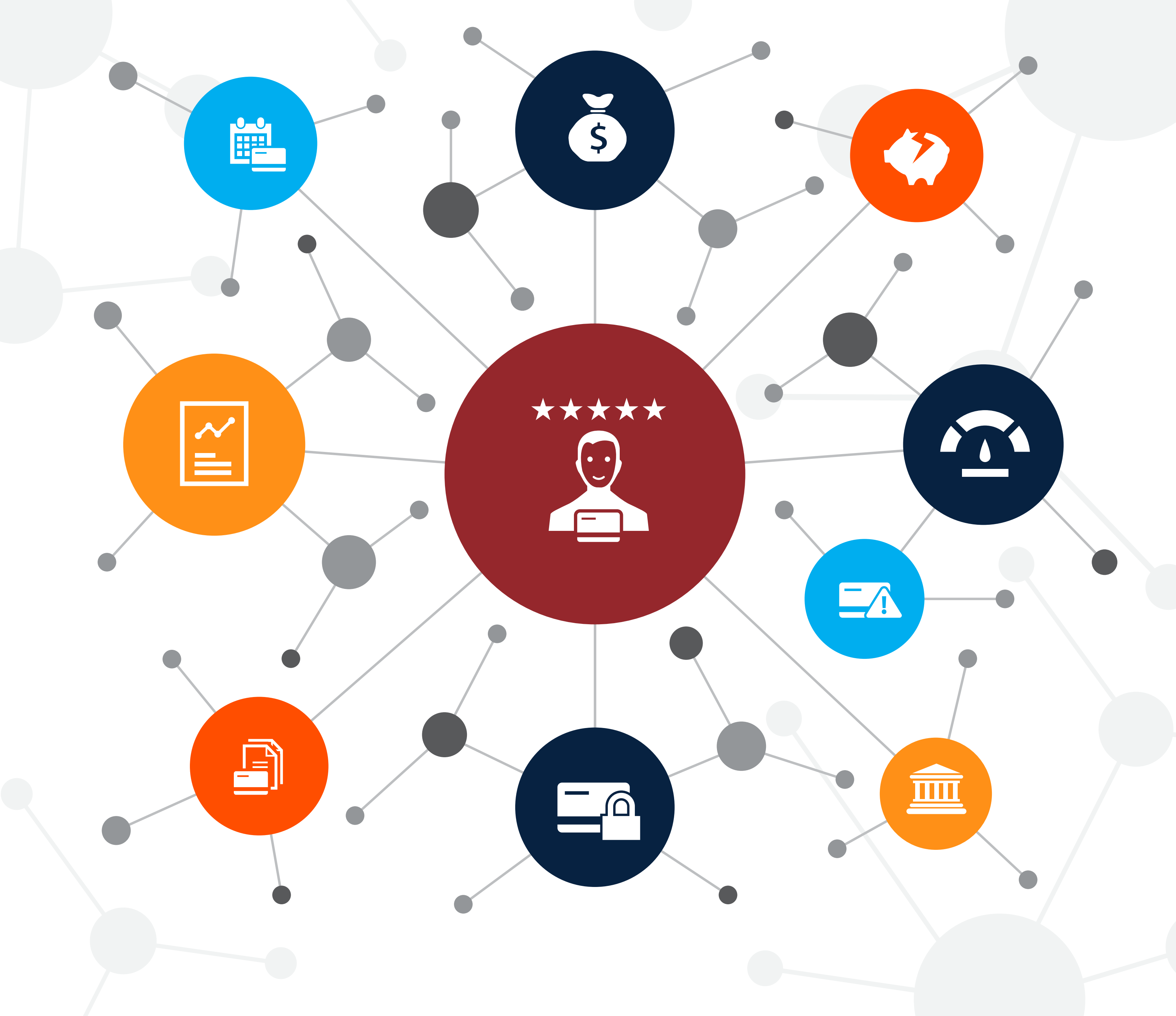
Local interpretable model-agnostic explanations (LIME) is a method for fitting local, interpretable models that can explain single predictions of any black box algorithm (Ribeiro, Singh, and Guestrin 2016).

LIME observes the effect of variations in the input data on the model. LIME perturbs samples of input data and the associated black box algorithm's predictions. It then trains an interpretable model weighted by the similarity of the sampled instances to the instance of interest (Champandard n.d.).

The LIME model can be any interpretable model that provides a good approximation of the black box algorithm locally.

Figure B.2: Example of Individual Conditional Expectation Plot





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