CRD Association Japan

Enhancement of Banks' Lending and Credit Risk Assessment:

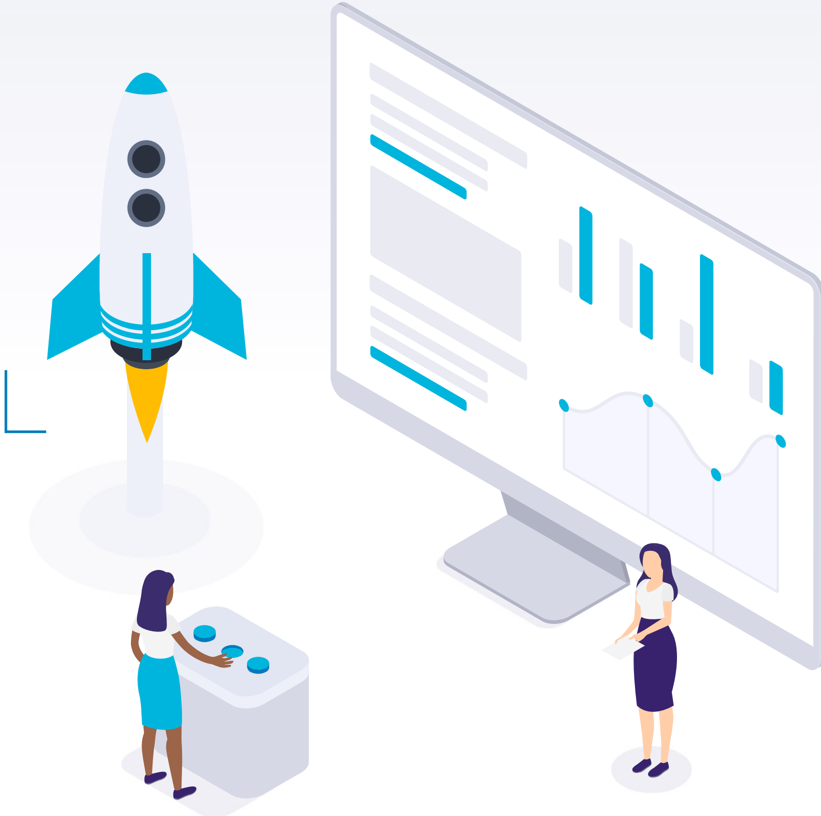
Scoring Model Using Machine Learning & Transaction data

Contents

- Benefits & Applications of Machine Learning (ML)
- Comparing ML Algorithms
- Data Exploration
- Model Selection
- Model Assessment
- Proof of Concept (POC)

CRD Association Japan

1 Benefits & Applications of ML



CRD Association Japan

Benefits of ML in lending & credit risk management

More Accurate Risk Assessment

ML can analyze vast amounts of data and are more powerful in finding data patterns that traditional credit scoring models may miss.

Enhanced Customer Experience

Faster Loans Approvals, tailored service due to insights into customers' behavior and preference

Monitoring and Alert system

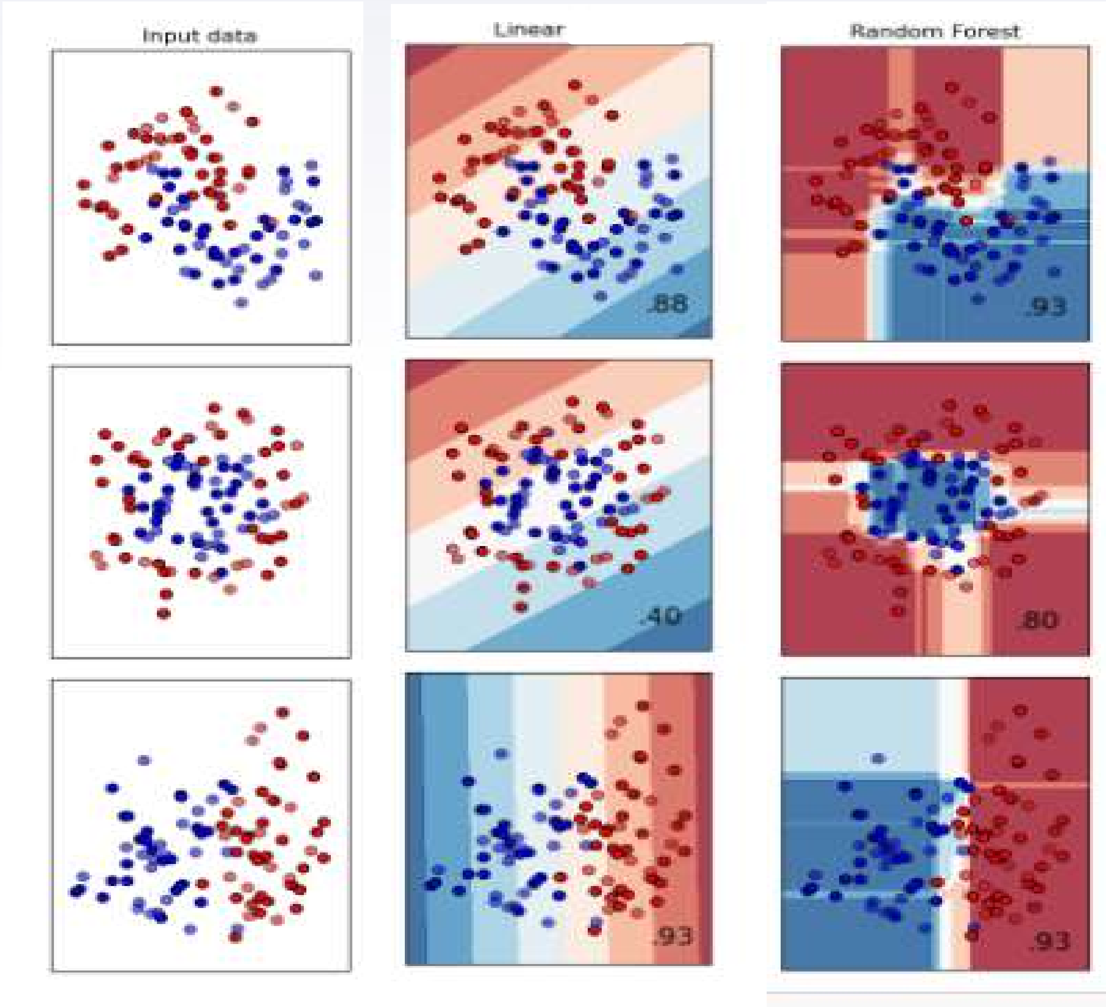
Alert basing on set rules generated by machine learning model. Example: cash holdings drop below certain level

Improved Fraud Detection

An ML model can analyze transaction data and detect anomalies that may indicate fraudulent activity.

More Accurate Risk Assessment

Use more sophisticated algorithms to pick up data patterns



Source: scikit-learn

More Accurate Risk Assessment

- Allow for analysis of big data: transaction data

>10 million deposits accounts

large regional banks in Japan

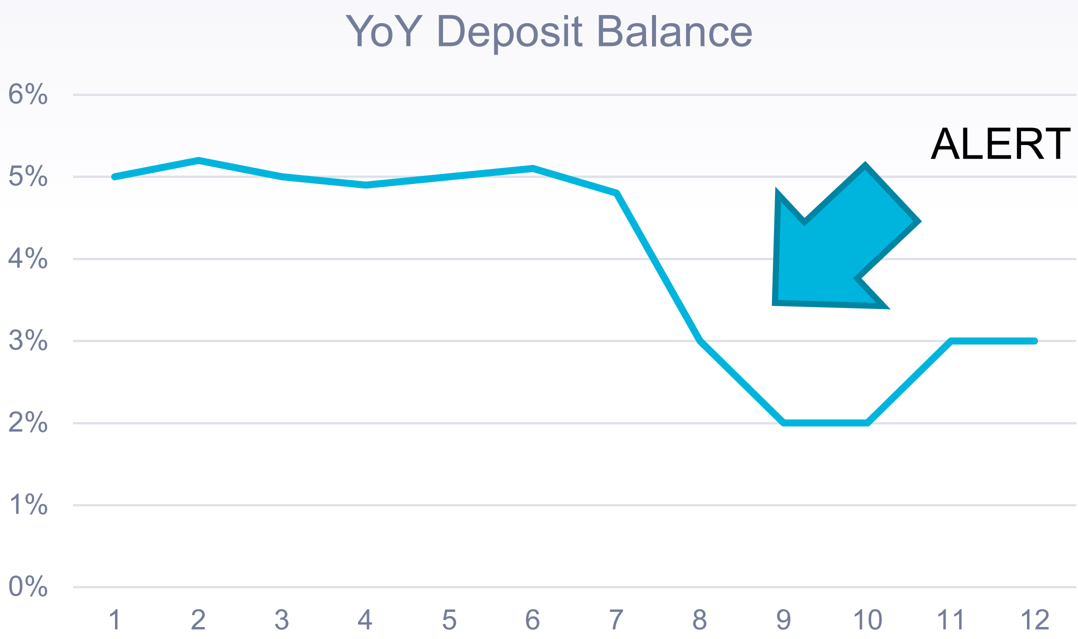
>1.1 billion transactions per year

>12,500 transactions per hour

That's a lot of data!

Monitoring and Alert system

EXAMPLE



CRD Association Japan

2 Comparing ML algorithms

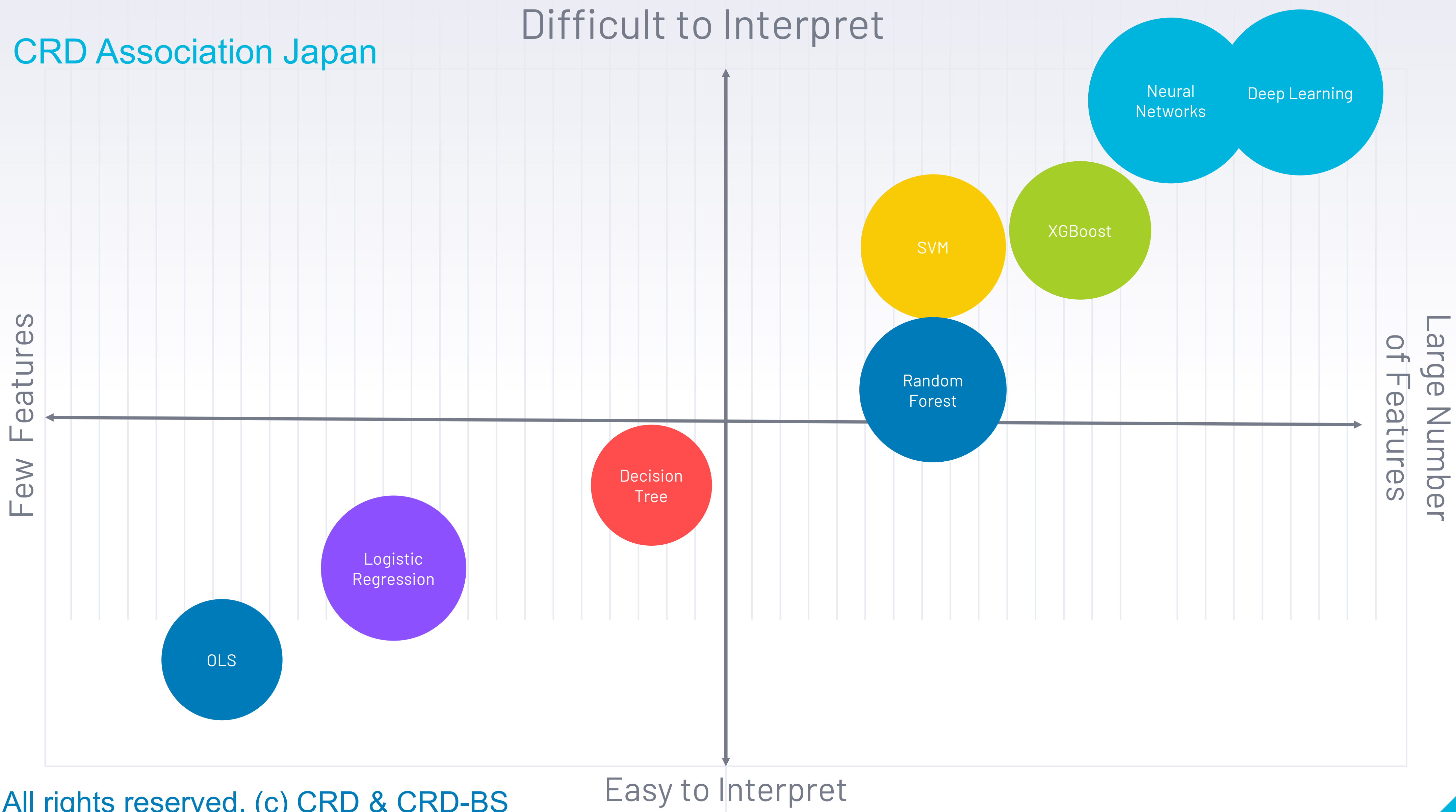
General terms

- Regression : $Y = a + b*x$
- Y:
  - binary or categorical (ex: default or non-default, malignant or not) → predicted classifier
  - continuous (ex: stock price, oil price) → predicted estimator
- x: continuous or categorical information used for prediction → also called model **variables** or **features**
- b: coefficients or parameters

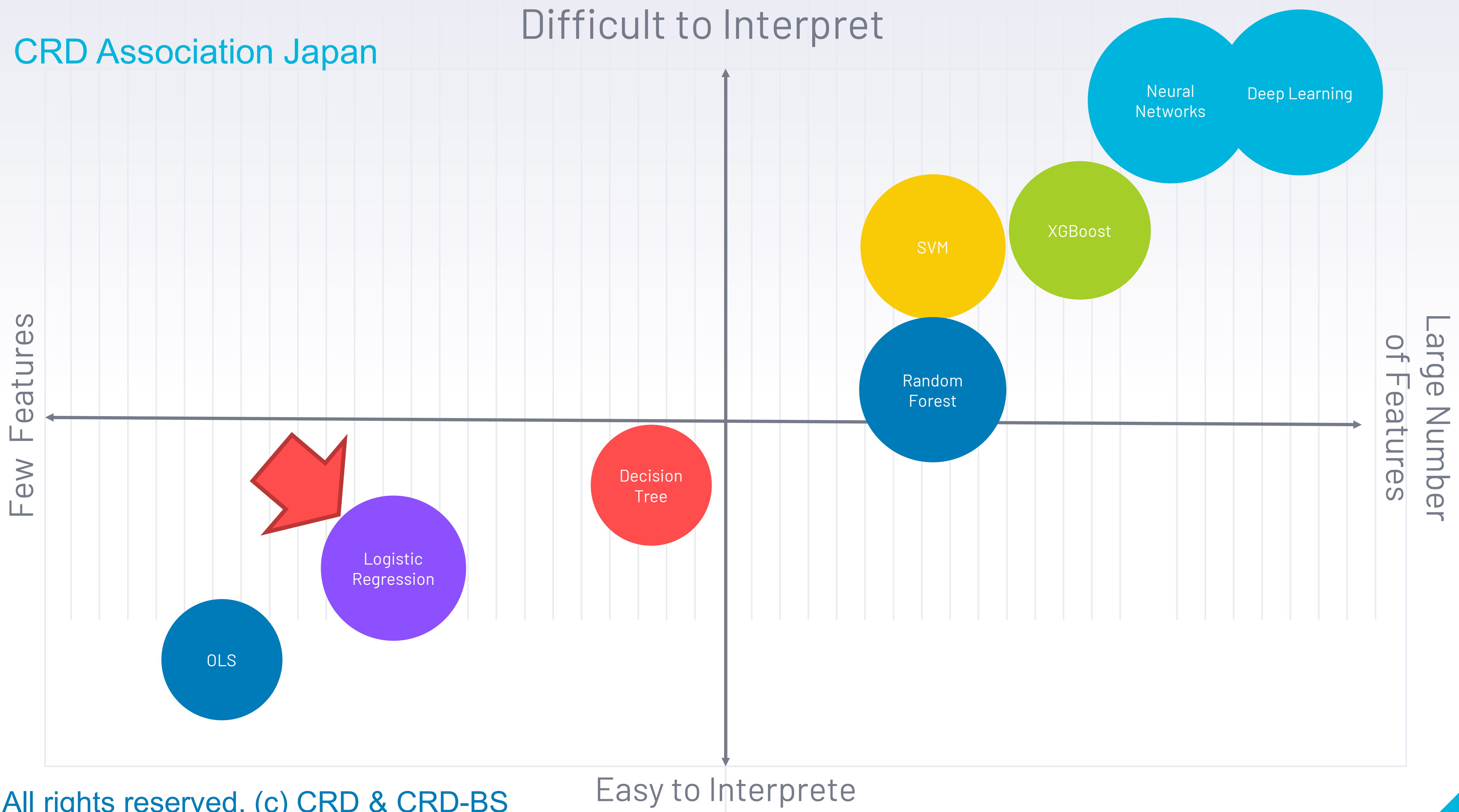
Example: Y is default or non default

x are financial indexes/ industry/ location/ owners' education

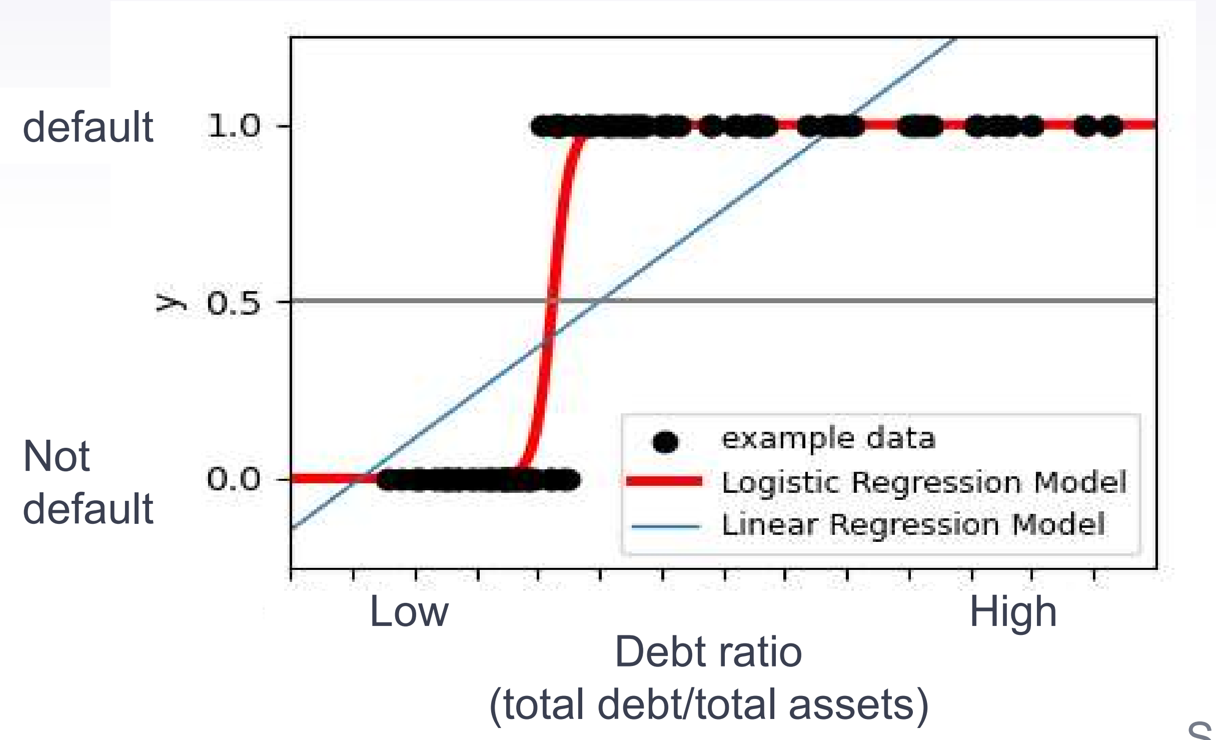
CRD Association Japan



CRD Association Japan



Logistic curve

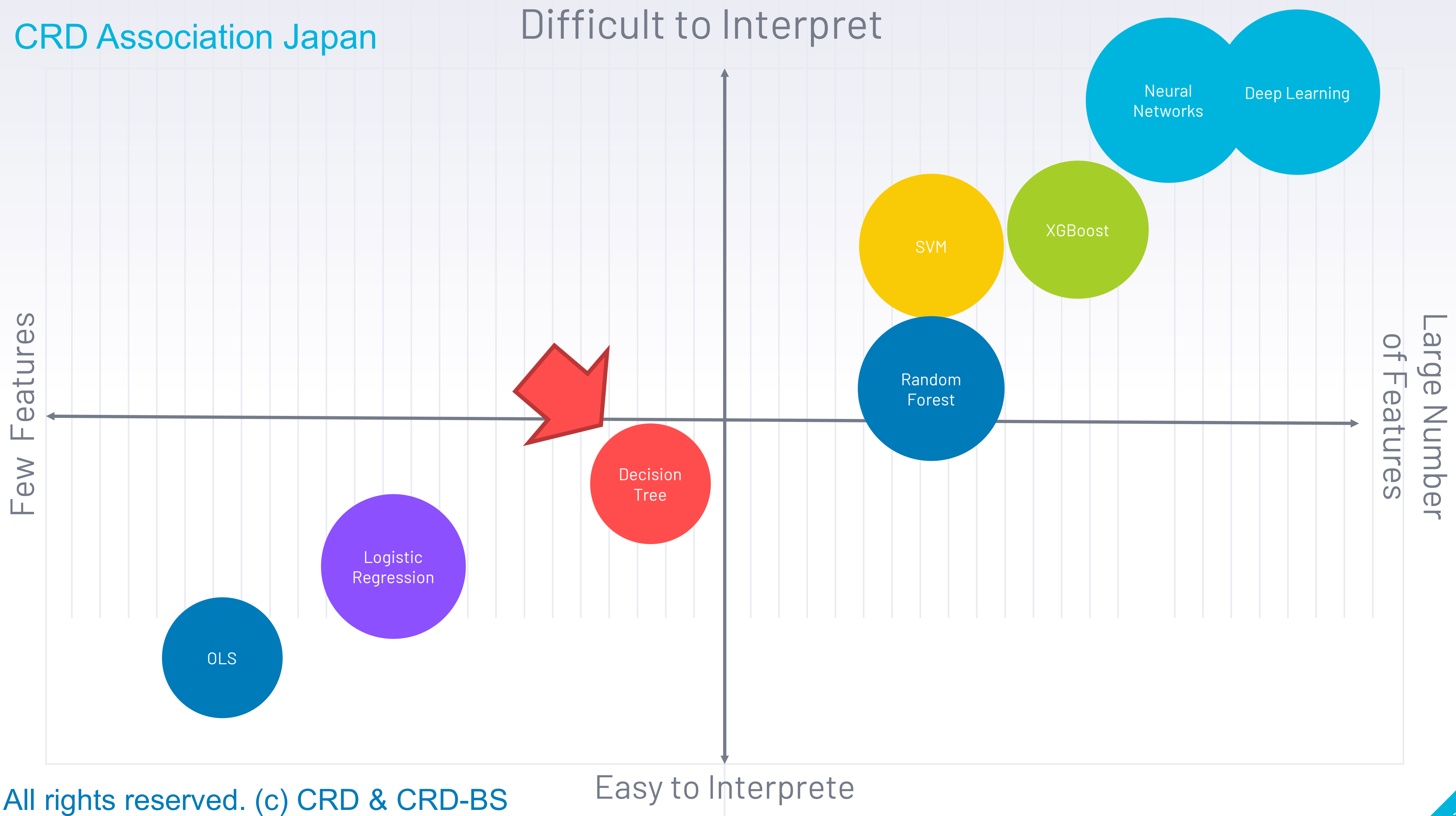


Source: scikit-learn

Logistic Regression

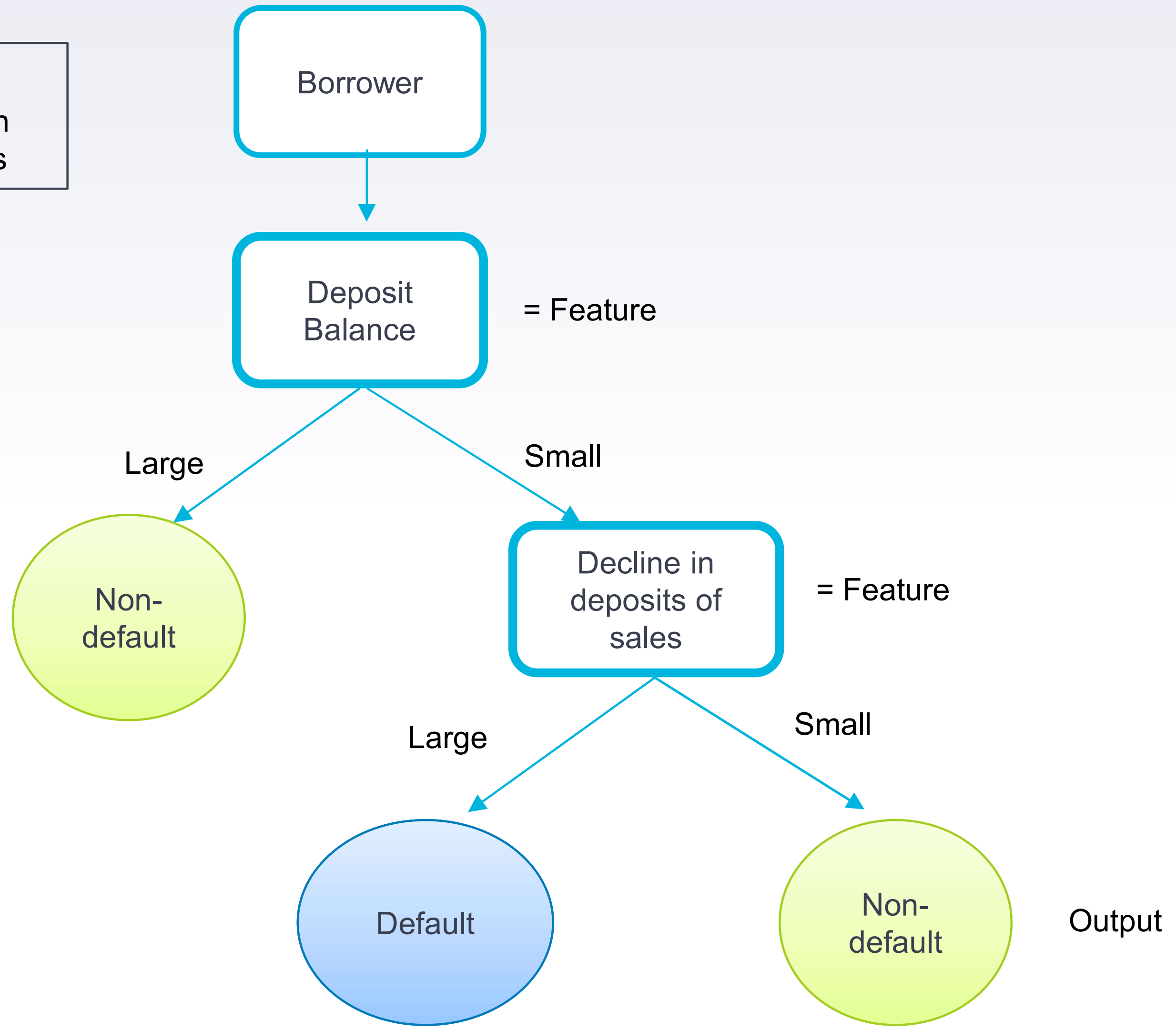
Applications	Pros	Cons
Predicting loan default probability, assessing credit risk of new applicants, identifying factors that contribute to credit risk	**Simple and interpretable**, good for binary classification, can handle large datasets with **limited number of features**	Requires a relatively large sample size in order to produce reliable and stable estimates of the coefficients. If the sample size is too small, the estimates may be unreliable or unstable

CRD Association Japan



Decision tree

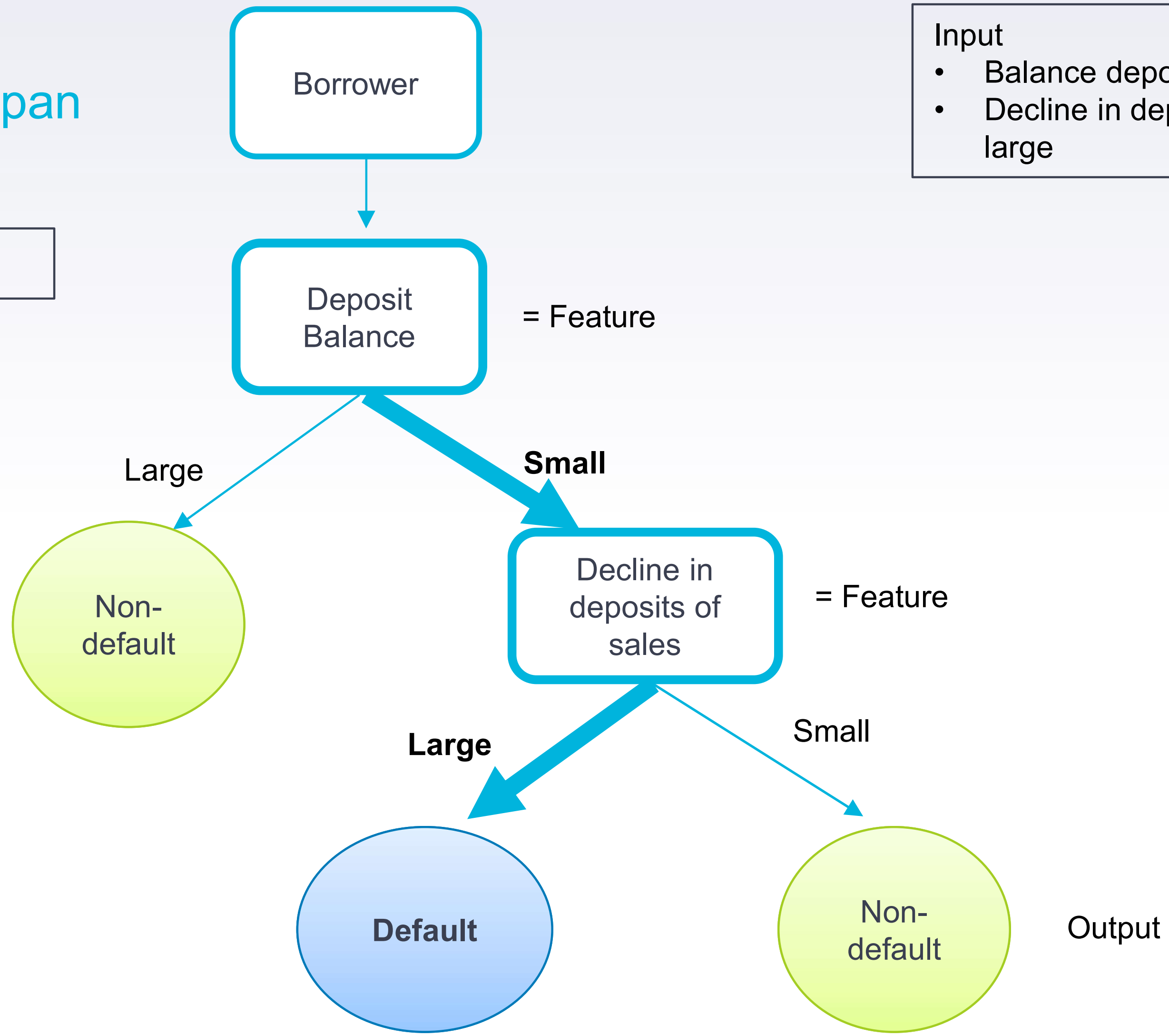
- Determine outcome based on one or more feature/variables



PD: probability of default

CRD Association Japan

Decision tree



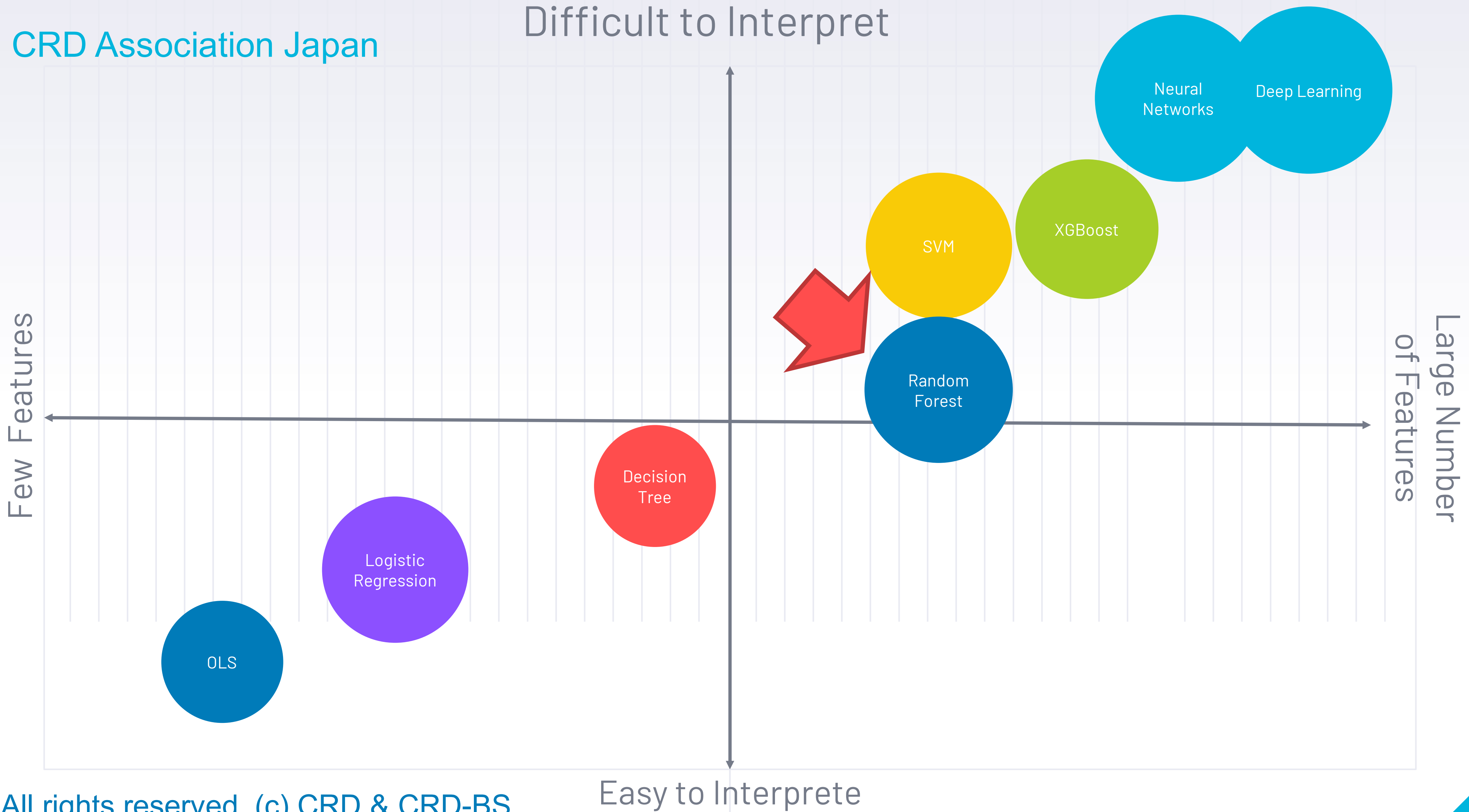
Input
- Balance deposit=small
- Decline in deposits of sales = large

PD: probability of default

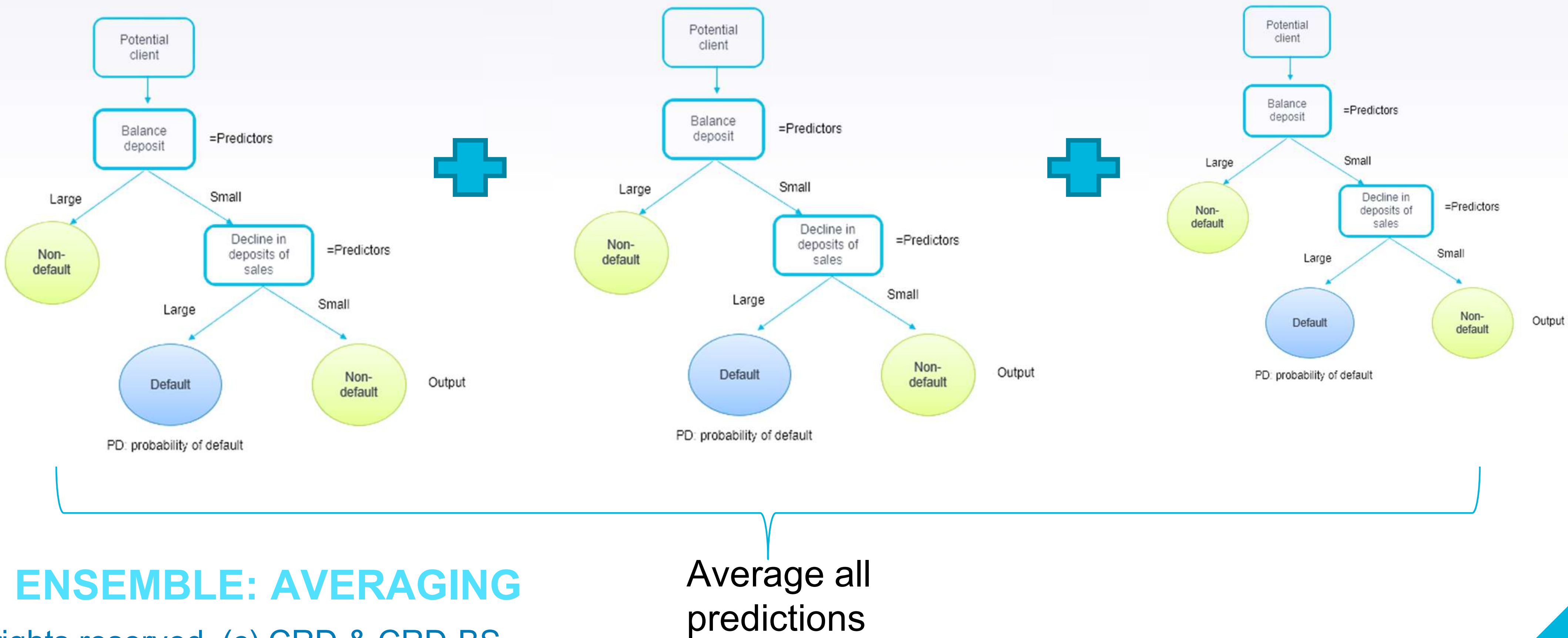
Decision Tree

Applications	Pros	Cons
Initial exploration of data, feature selection, binary or multi-class classification tasks with relatively simple data	**Interpretable and easy to understand**	Tends to overfit, sensitive to noise in the data, may not generalize well to new data

CRD Association Japan



Random Forest

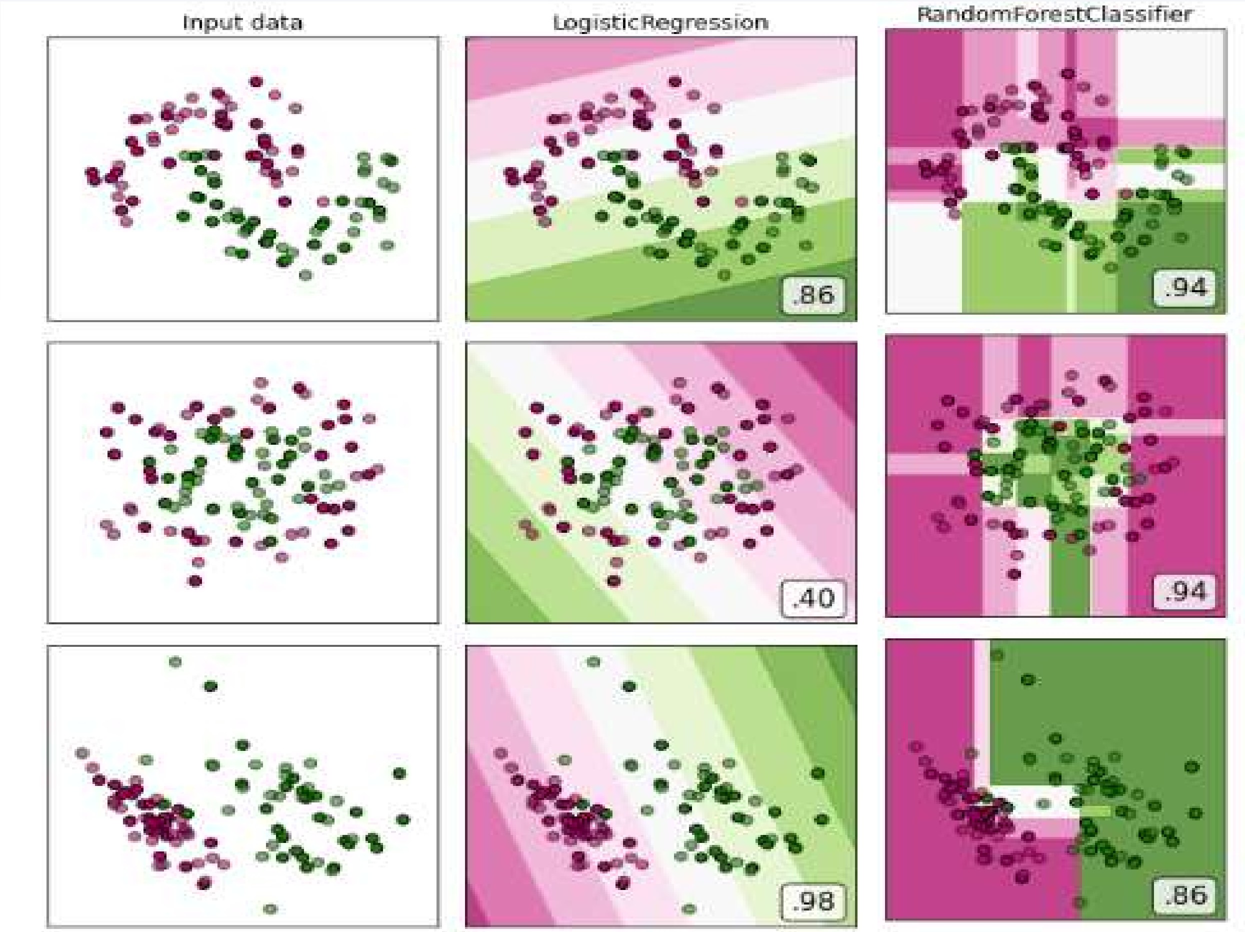


ENSEMBLE: AVERAGING

Random Forest

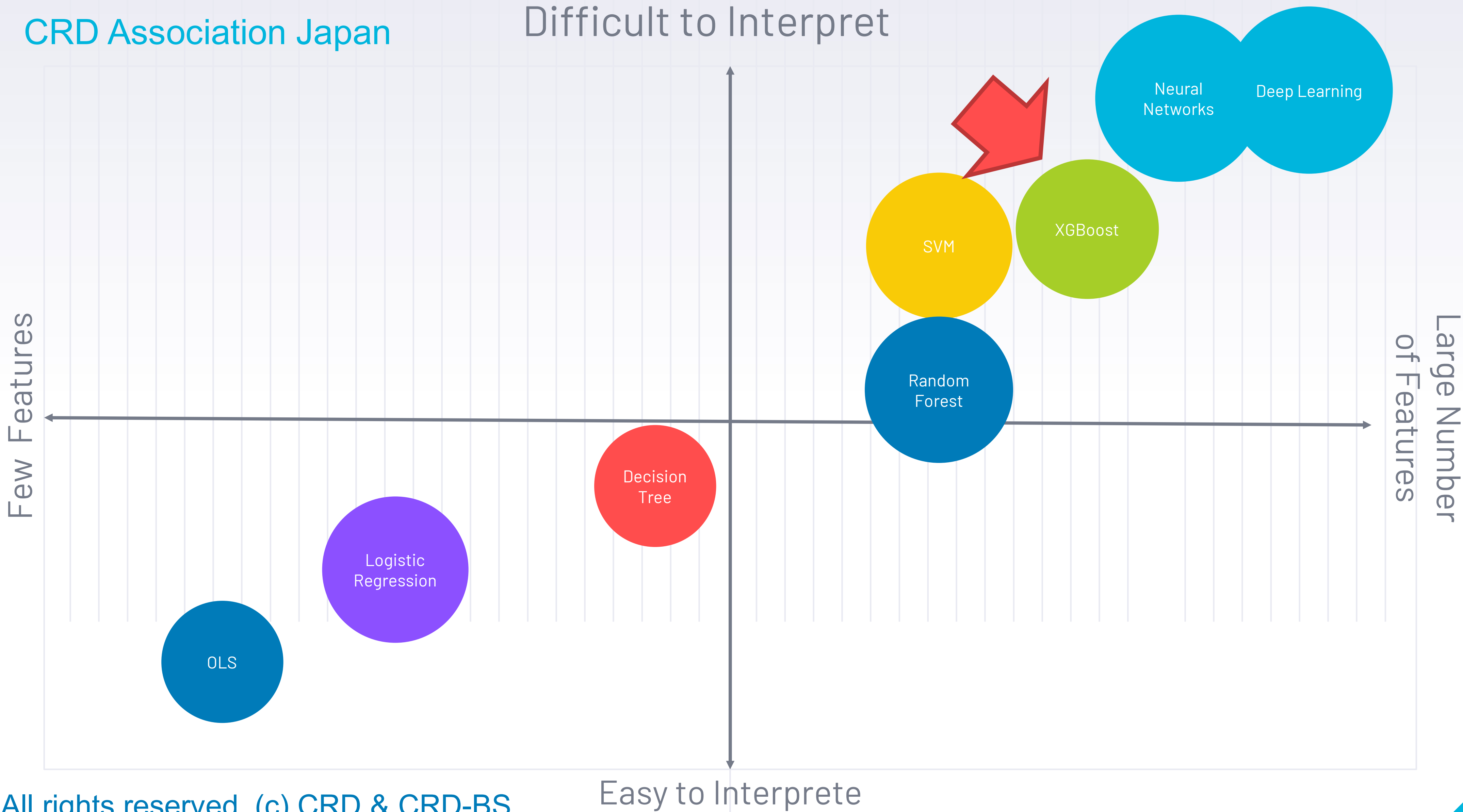
Applications	Pros	Cons
Binary or multi-class classification tasks, regression tasks, feature selection, anomaly detection	Handles non-linear relationships**, robust against overfitting**, can handle large data, **provides feature importance ranking**	Less interpretable than single decision trees, slower training time than single decision trees, may not perform as well on imbalanced datasets

Random Forest

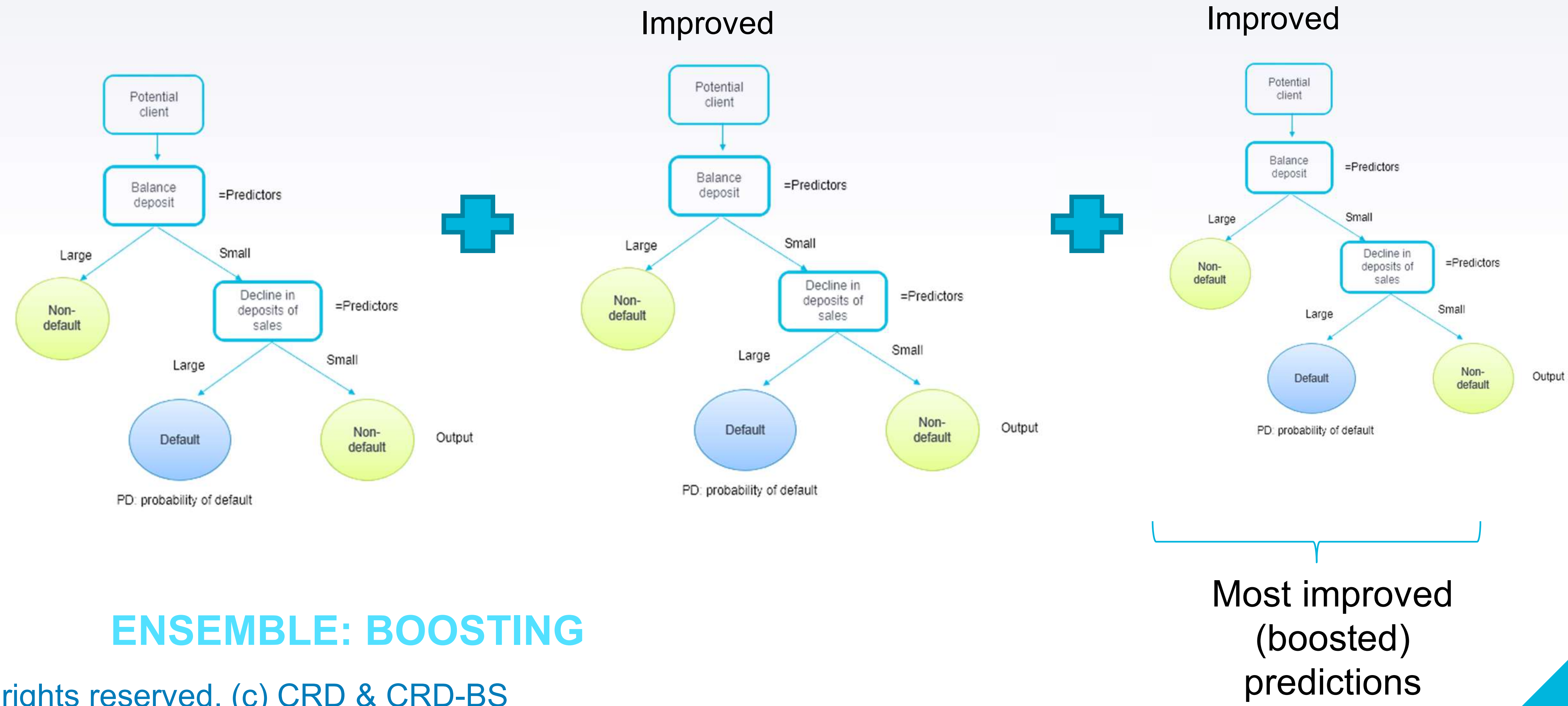


Source: scikit-learn

CRD Association Japan



XGBoost

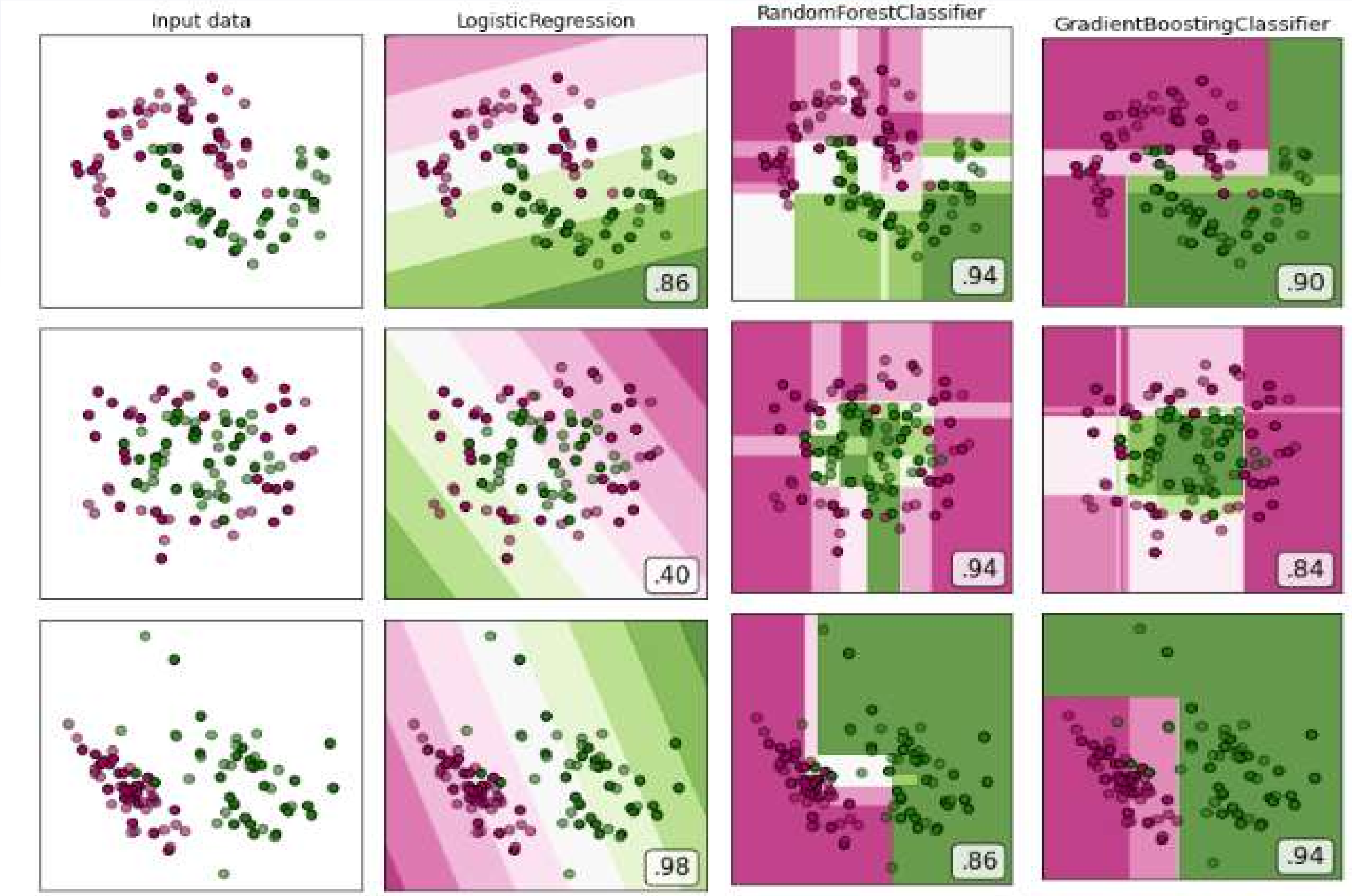


ENSEMBLE: BOOSTING

XGBoost

Applications	Pros	Cons
Fraud detection, credit scoring, anti-money laundering, anomaly detection	**Can handle large, high-dimensional datasets, provides feature importance ranking**	Can be computationally expensive for large datasets, requires careful tuning of hyperparameters, can be prone to overfitting if not properly regularized

XGBoost



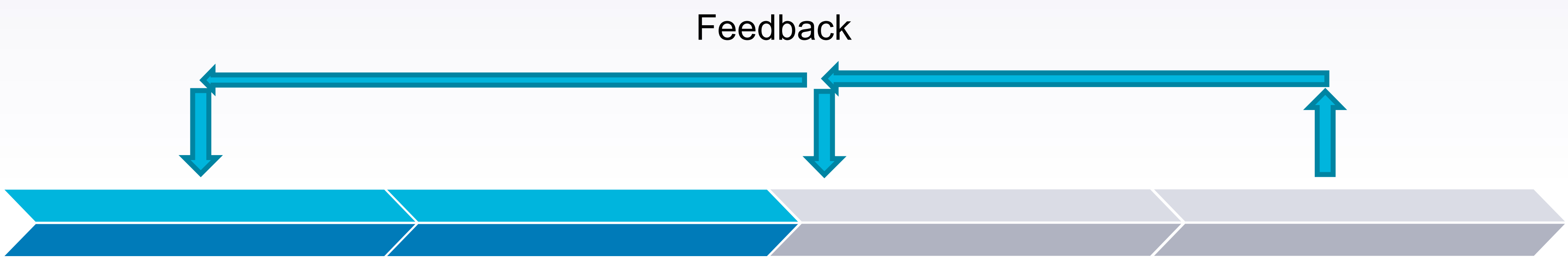
Source: scikit-learn

CRD Association Japan

3 Data Exploration

CRD Association Japan

Model Building Process



Data preparation

Data exploration, data collection, data cleaning

Variable/Feature Selection

Feature selection, feature importance

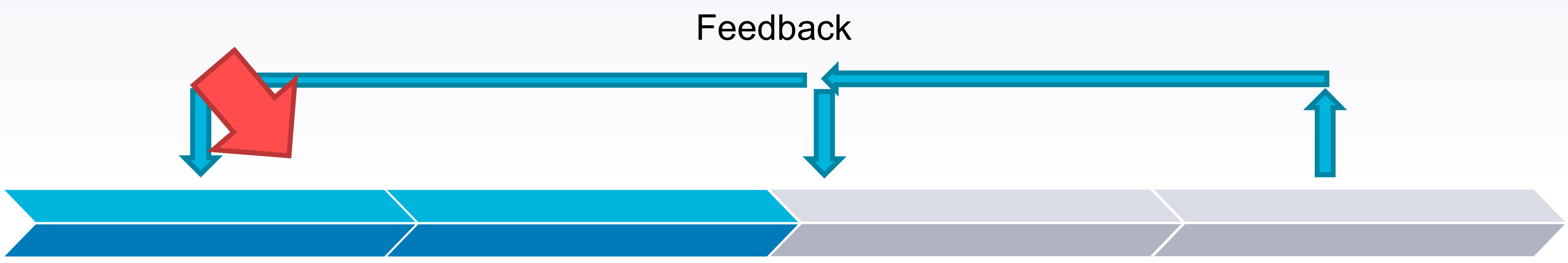
Model Building

Model Selection, Parameter Tuning, Grid Search

Model Validation

Cross-validation, Out-of-sample testing

Model Building Process



Data preparation

Data exploration, data collection, data cleaning

Variable/Feature Selection

Feature importance

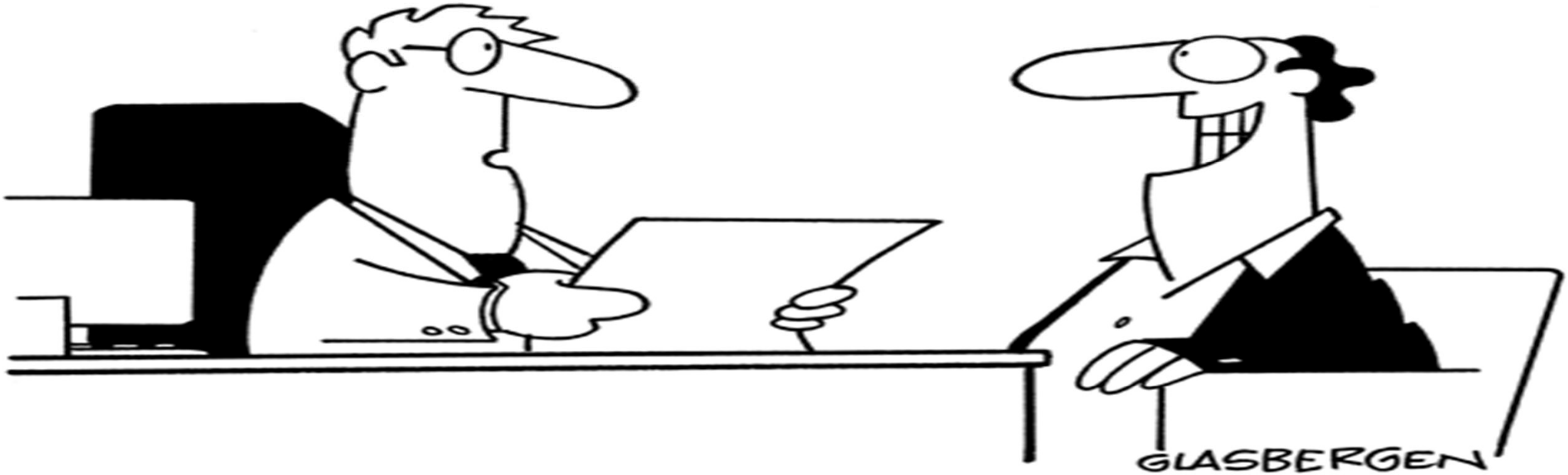
Model Building

Model Selection, Parameter Tuning, Grid Search

Model Validation

In-sample testing, Out-of-sample testing

LOANS



"Any other collateral besides your heart of gold and million dollar smile?"

Alternative Data

Transaction Data

Transaction data from bank accounts

E-commerce data

Purchase history from e-commerce websites

GPS data

Location tracking smart phones

Data from wearable technology and other connected devices.

Review data

Google Reviews, Yelp

Particularly for small businesses in services sector to assess reputation and financial stability of the business

Social Media data

SNS use frequency and connections

Digital marketing

Utility & Rental payments

Utility and telecom payments

Rental payment history

Transaction Data from bank account

BANK ACCOUNT'S TRANSACTION DATA

Transaction Data

1. Sales revenue from products or services
2. Rental income from property owned by the business
3. Investment income from stocks, bonds, or mutual funds
4. Interest income from savings accounts or other financial instruments
5. Capital contributions from owners or investors
6. Grants or other forms of funding from government or non-profit organizations
7. Insurance settlements or payouts
8. Licensing fees for the use of the business's intellectual property
9. Royalties from the sale of products or services
10. Rebates or refunds from suppliers or vendors
11. Return of capital from investments
12. Dividends from stocks or other equity holdings
13. Settlements from legal claims or disputes
14. Proceeds from the sale of assets or property
15. Inheritance or other windfalls
16. Accounts receivable collections
17. Gift or donation income
18. Crowdfunding or other forms of online fundraising
19. Prepaid or advance payments from customers or clients
20. Resale or consignment revenue from selling goods on behalf of others

Inflows

EXAMPLE

Transaction Data

Outflows

EXAMPLE

1. Salary payments
2. Payment of supplier invoices
3. Rent payments
4. Utility bill payments
5. Payment of taxes and duties
6. Loan repayments
7. Investment and securities purchases
8. Purchase of raw materials
9. Purchase of office equipment and supplies
10. Payment for consulting services
11. Payment for legal services
12. Payment for accounting services
13. Payment for advertising and marketing services
14. Payment for IT services and software
15. Payment for travel and entertainment expenses
16. Payment for insurance premiums
17. Payment for freight and shipping charges
18. Payment for maintenance and repair services
19. Payment for office rental
20. Payment for professional development and training expenses.

Transaction coding system

- Japan

Zengin System

- US

Fedwire Funds Service

Automated Clearing House

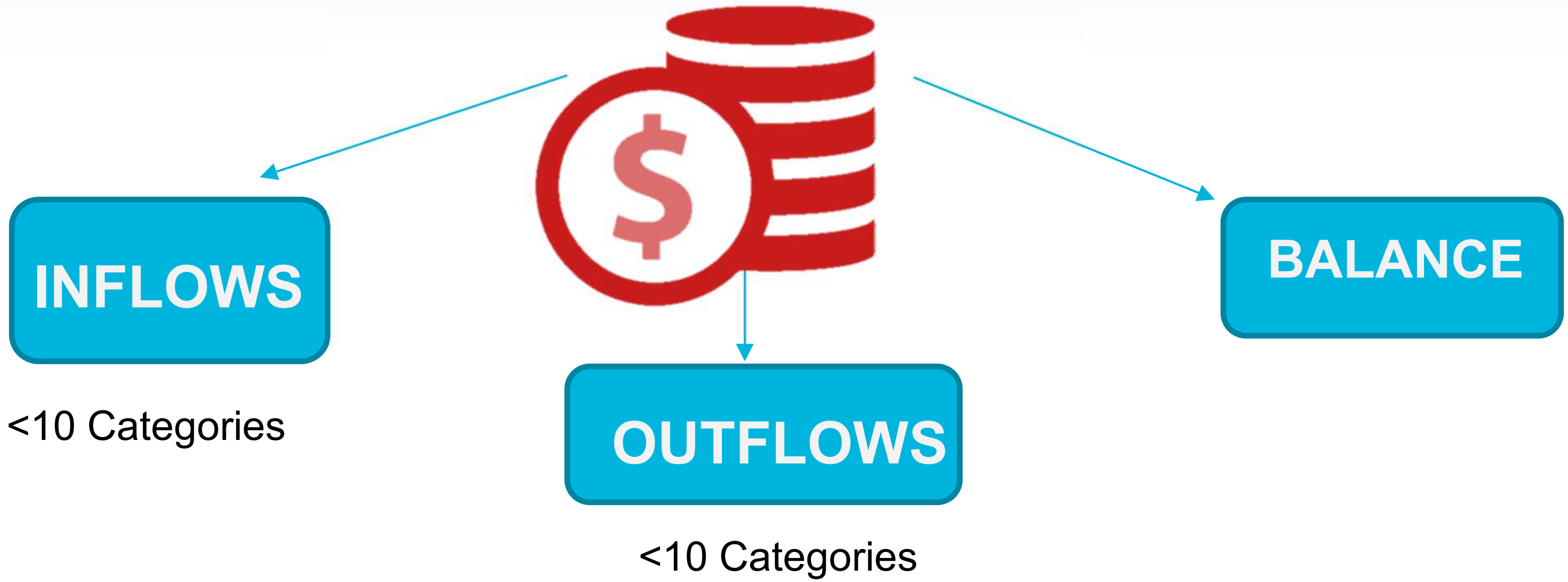
- Taiwan

Financial Information eXchange (FISC) system

Japan	US	Taiwan
capture payment, receipt, transfer, direct debit, and credit card transactions	real-time system for settlement with transaction purpose classification coding	primarily domestically used by financial institutions for electronic funds transfers

Classify transaction code

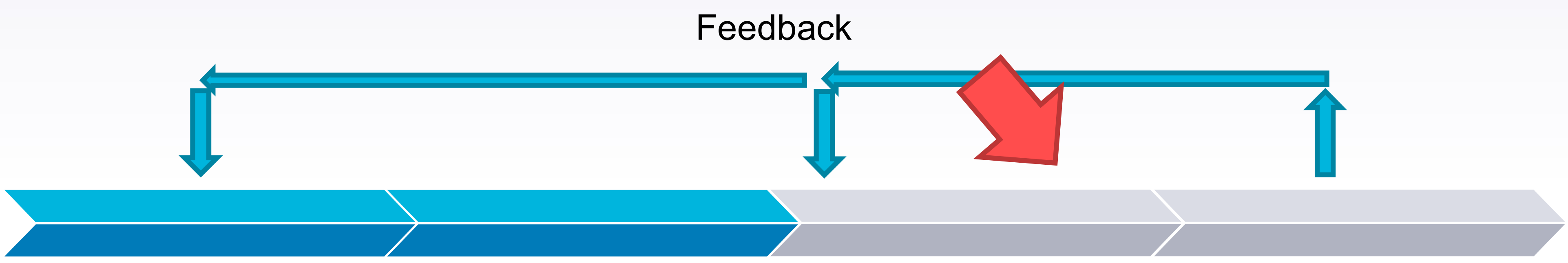
Regrouping into transaction purpose basing on experience/expertise



4 Model Selection

CRD Association Japan

Model Building Process



Data preparation

Data exploration, data collection, data cleaning

Variable/Feature Selection

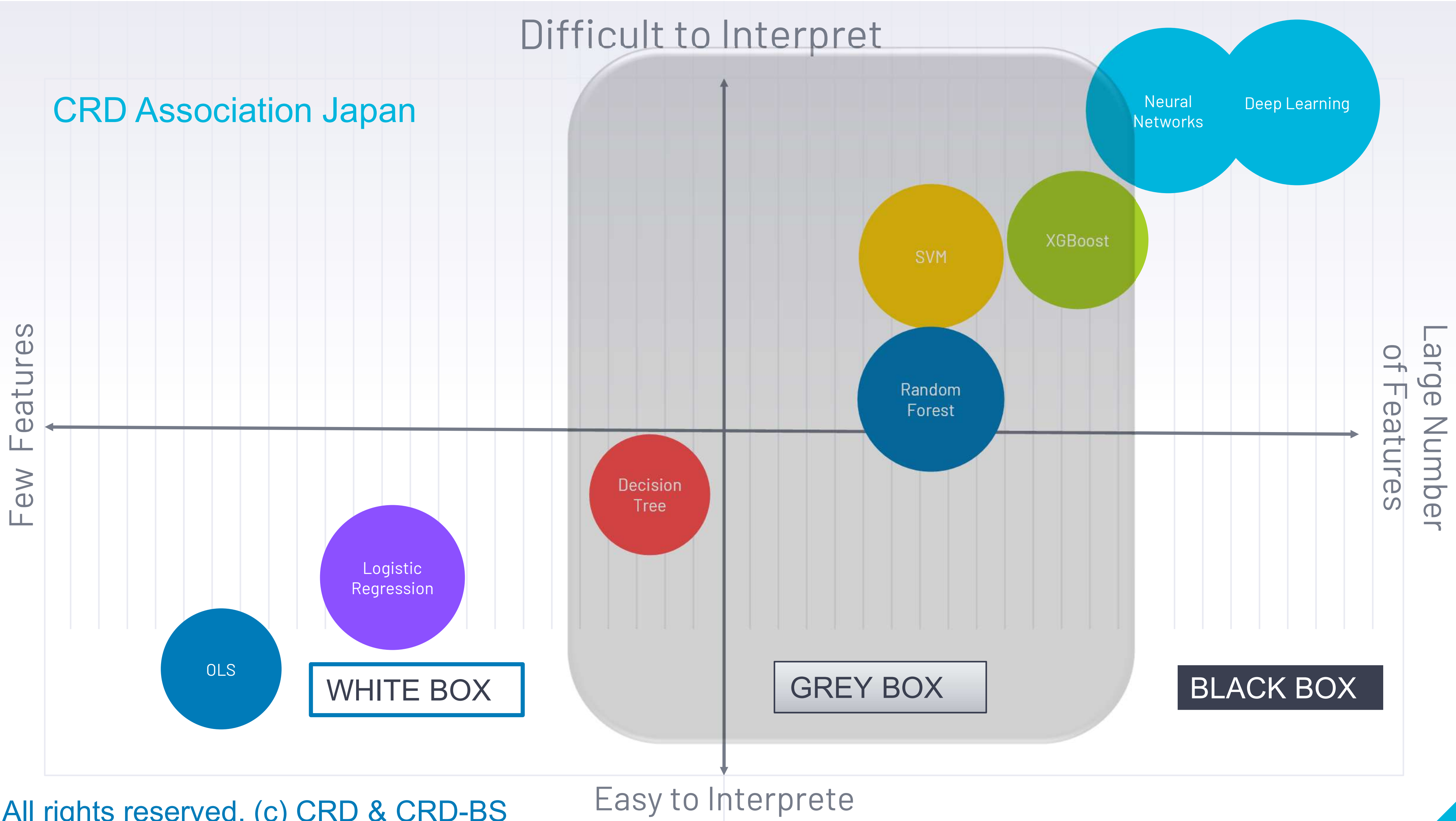
Feature importance

Model Building

Model Selection, Parameter Tuning, Grid Search, Model Assessment

Model Validation

In-sample testing, Out-of-sample testing



Difficult to Interpret
CRD Association Japan
Neural Networks
Deep Learning
SVM
XGBoost
Few Features
Random Forest
Large Number of Features
Decision Tree
Logistic Regression
OLS
WHITE BOX
GREY BOX
BLACK BOX
Easy to Interprete

Model Selection

Avoid Blackbox in credit risk management

Deep Learning

NN, CNN

Grey box is ok

Random Forest

Boosting Algorithms: XGBoost, Adaboost

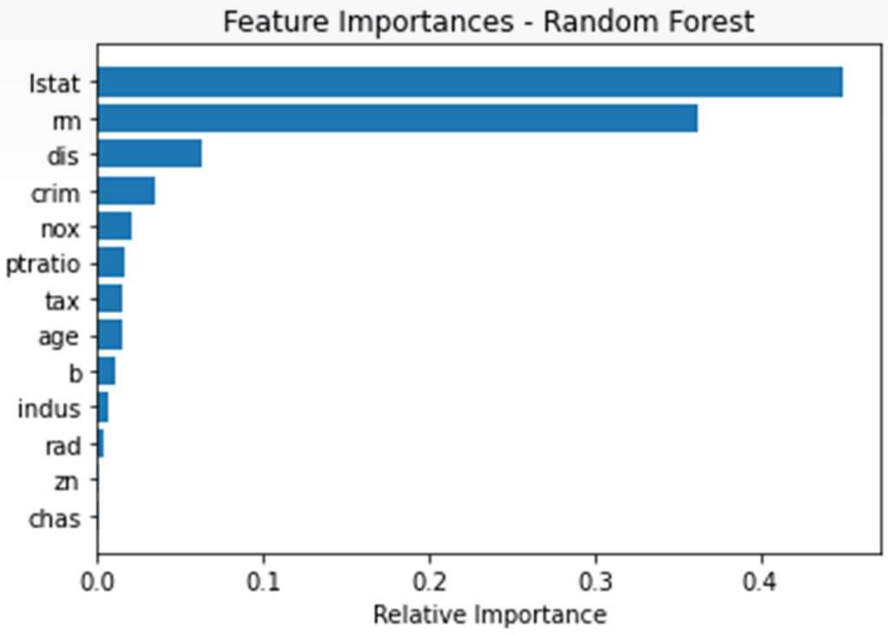
Model Selection

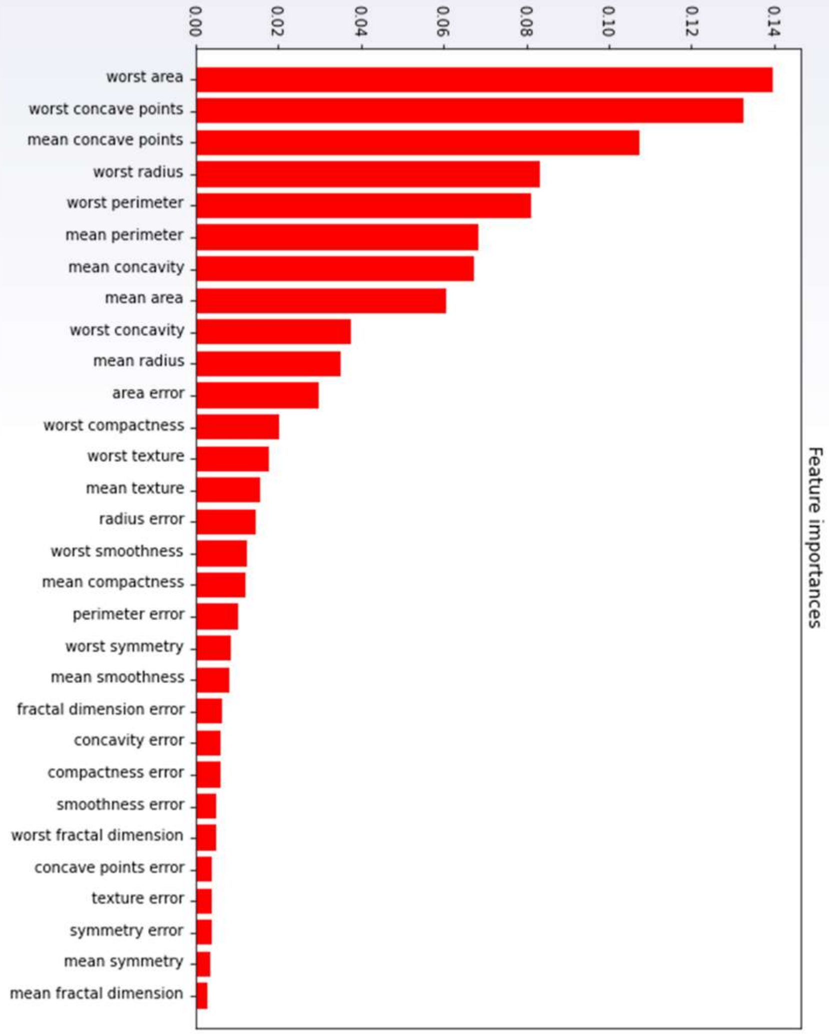
- Avoid Blackbox in credit risk management
  - Lack of interpretability and explainability
  - Lack of human oversight
  - Regulatory concern

- Grey box is ok
  - More powerful than white-box
  - Feature importance helps with interpretation

CRD Association Japan

Features and Features importance

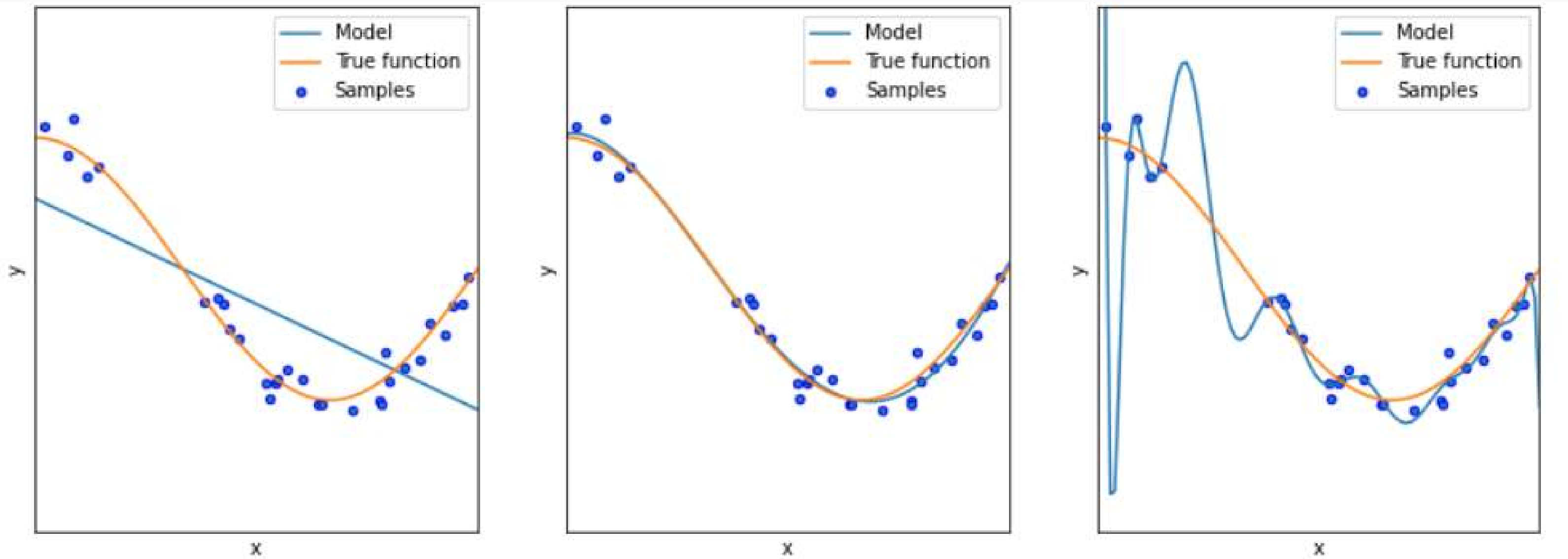




EXAMPLE

Source: scikit-learn

Underfitting and Overfitting



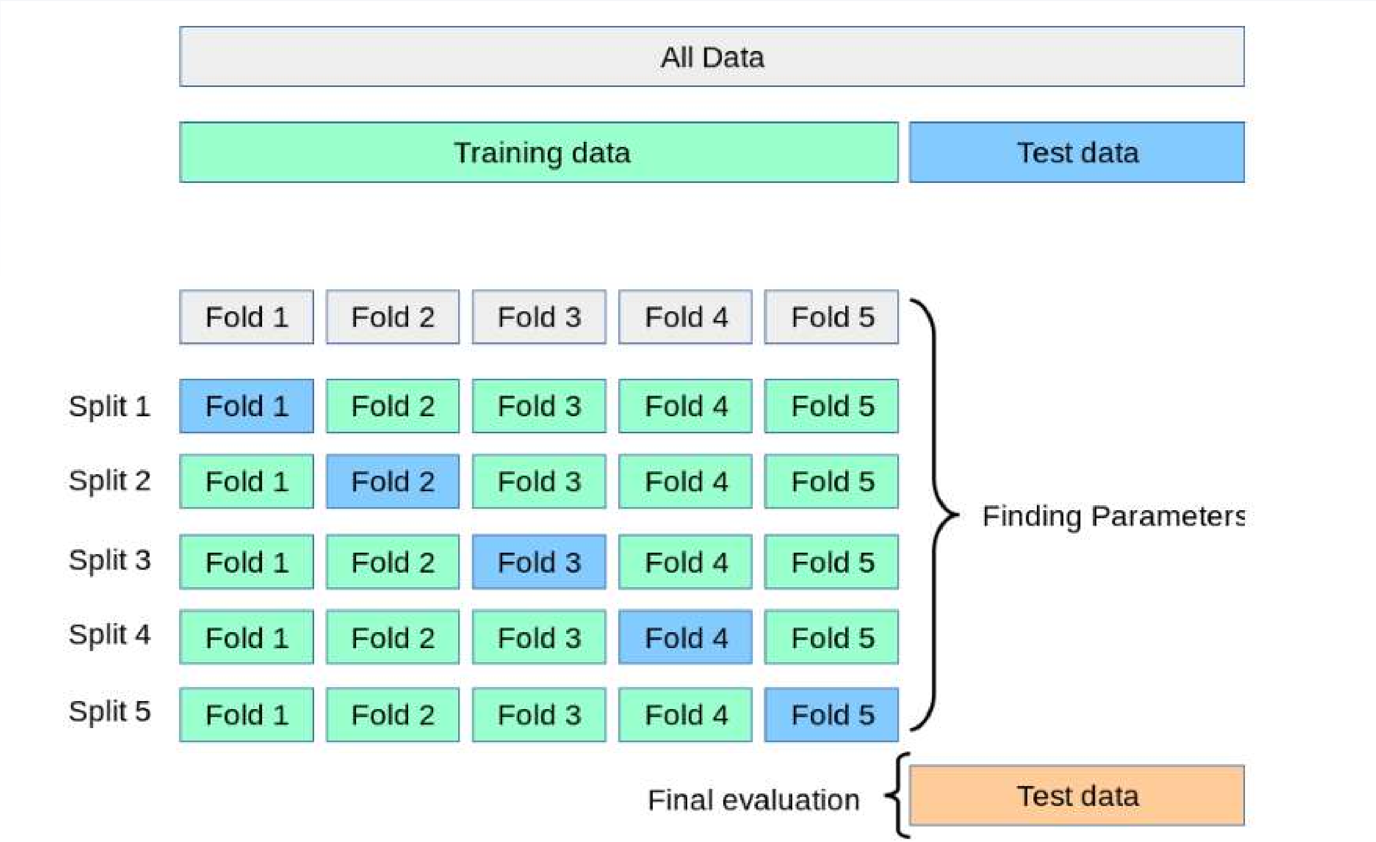
Underfitting

Fitting

Overfitting

Source: scikit-learn

Cross-validation



Source: scikit-learn

CRD Association Japan

5 Model Assessment

Model Assessment

INTERPRETABILITY

Do the features have correlation with default? Is this relationship explainable?

ACCURACY

How accurately can the model predict?

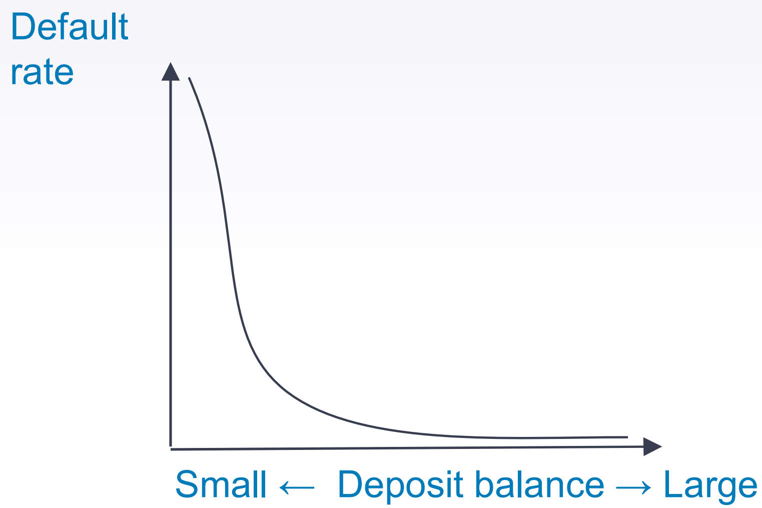
Can the bank upgrade or change the model when necessary?

MAINTENANCE

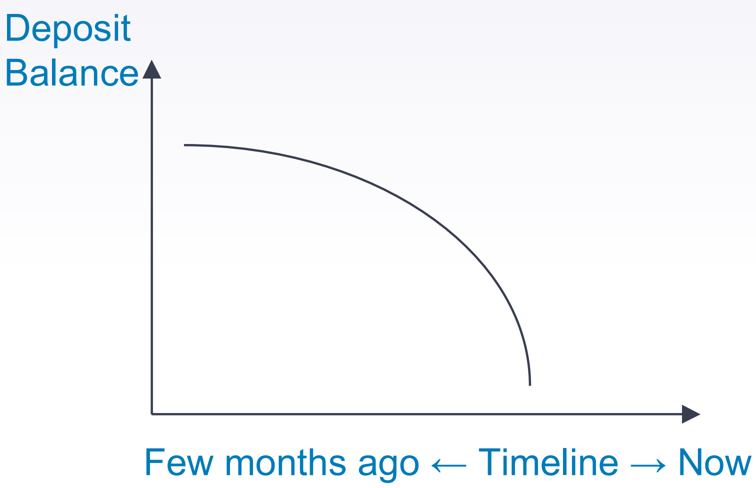
How does the model perform across time?

STABILITY

Interpretability: transaction data patterns



If the deposit balance near the time of valuation is large to a certain extent, default will be less likely



Decreasing recent balance of deposits signals default

Accuracy

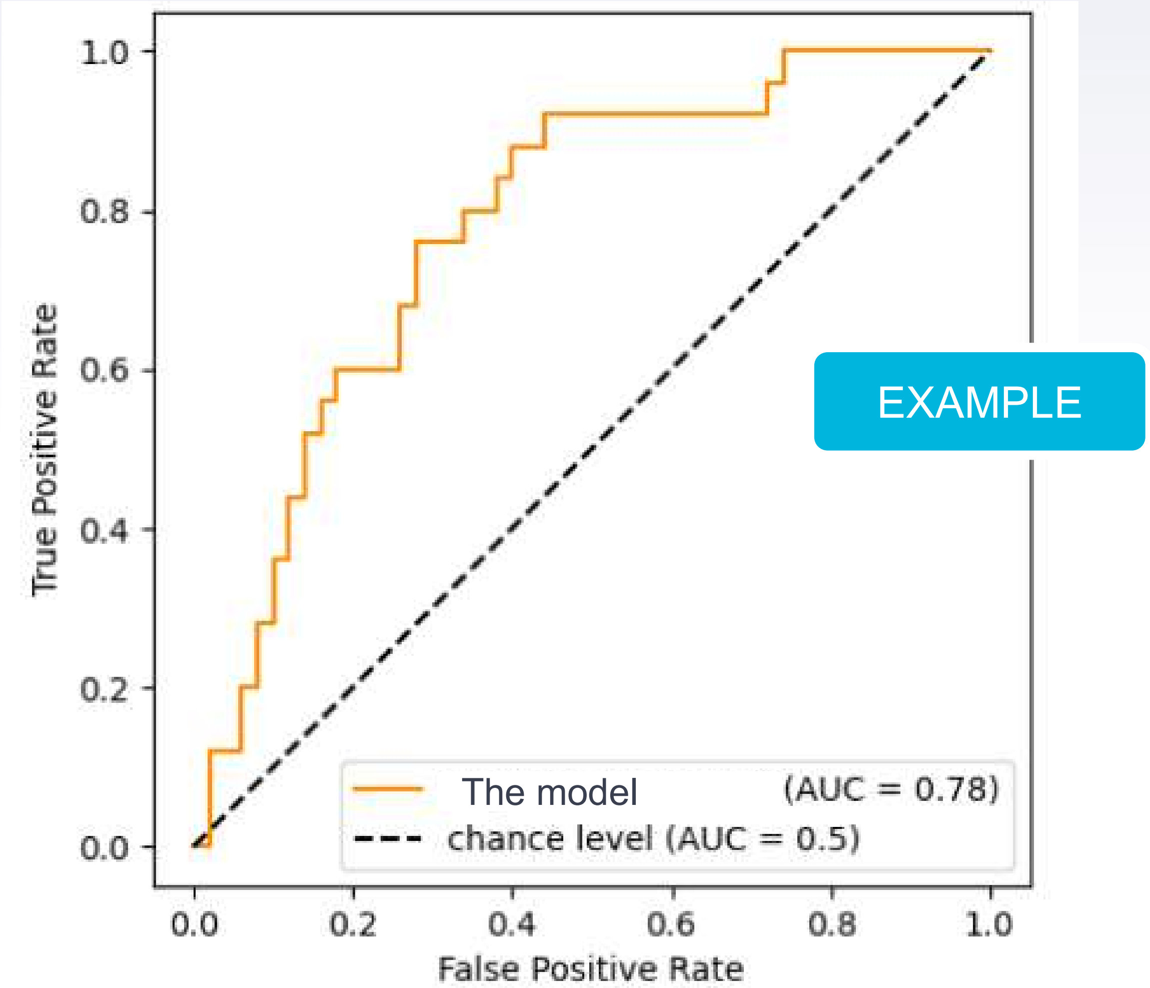
		Actual Class (Observation)	
		Default	Non-default
Predicted class (expectation)	Default	tp (true positive) Correct result	fp (false positive) Unexpected result
	Non-default	fn (false negative)	tn (true negative)

Receiver operating characteristic (ROC)

- True positive rate (sensitivity) = number of true positive /number of all obs
- True negative rate (Specificity) = number of true negative/number of all obs
- False positive rate = 1- true negative rate

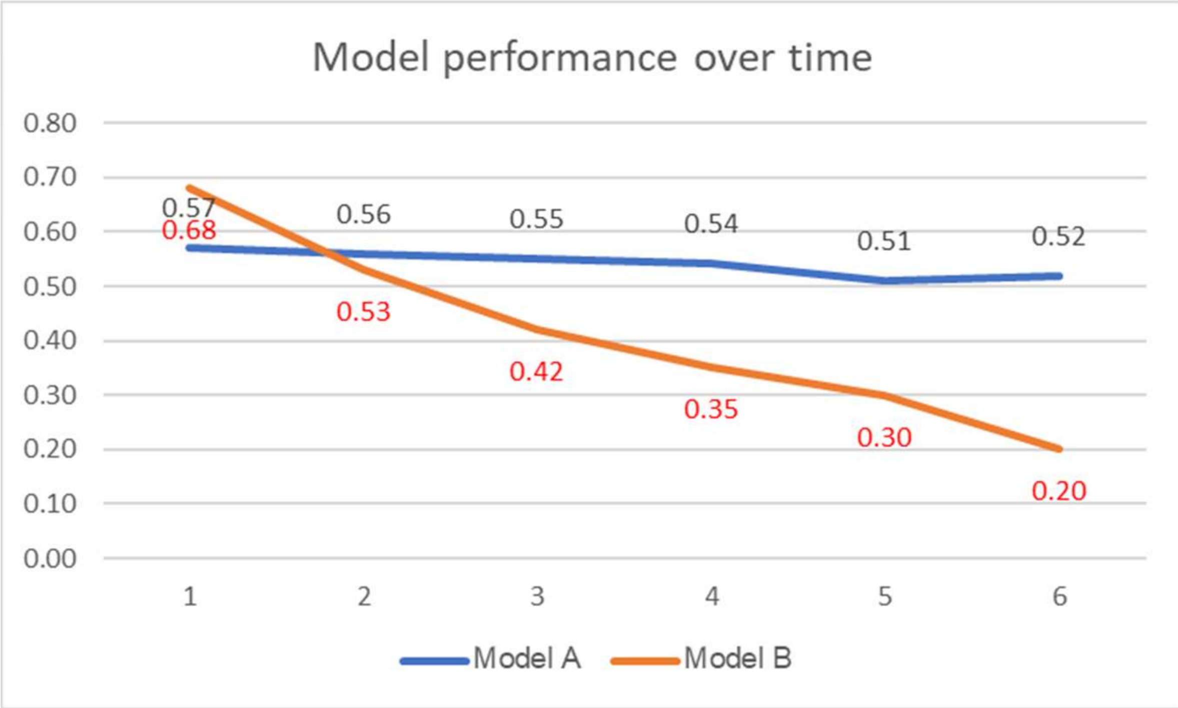
Area under the Receiver operating characteristic (ROC) curve = AUC

- Model's prediction power: AUC or AR
- The model: orange line
  - Example: AUC = 0.78
  - Accuracy Ratio = (AUC-0.5) *2=0.56
  - AR~Gini Coefficient
- Random model: 45 degree line
  - Example: AUC=0.5/AR=0



Source: scikit-learn

Stability: Out-of-sample validation



CRD Association Japan

6

Proof of Concept (POC)

Existing transaction credit scoring models in Japan

- CRD Association's Transaction Model
- Individual banks' models

CRD Association's Transaction Model

Model Algorithms

Random Forest

XGBoost

Data

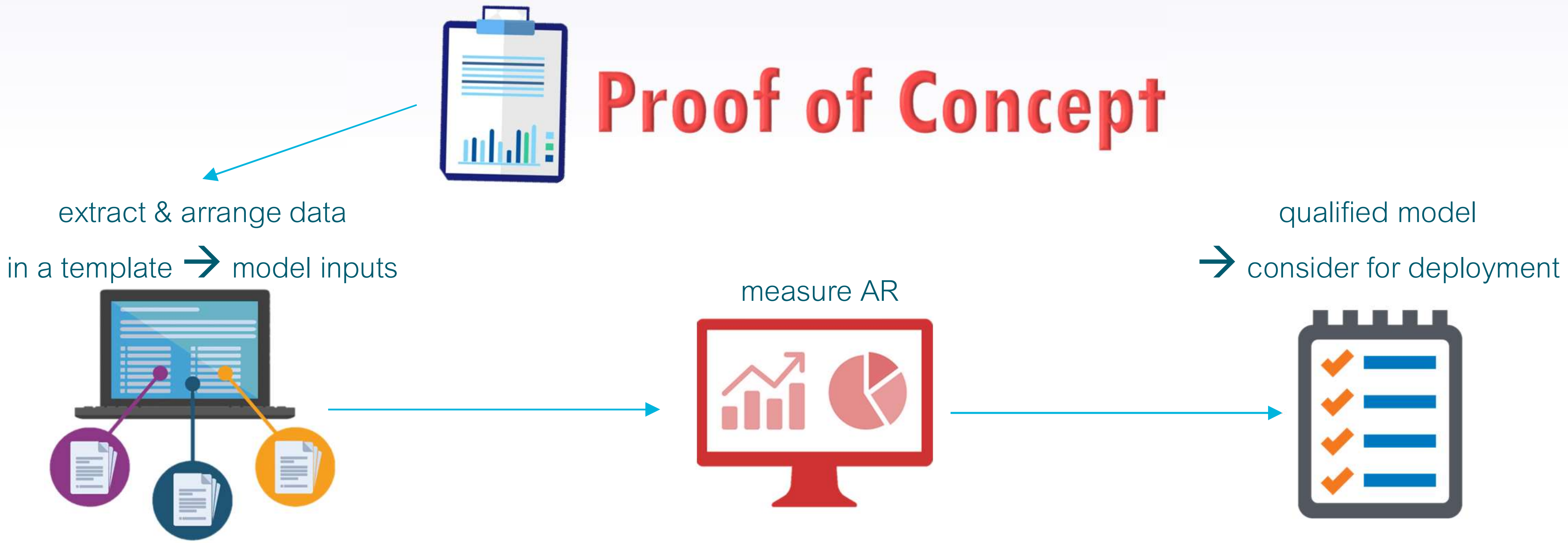
Transaction Data

6000 features

Model Peformance

Random forest (~350 decision trees): AUC>0.85 AR>0.7
XGBoost (~350 decision trees): AUC>0.85 AR>0.7

CRD Association Japan



Output of POC

- AR for the bank's entire dataset
- AR for detailed segments, such as sales size, industries, area, business type...
  - Ex: AR for retail sector, AR for micro businesses
- Scores for borrowers (if applicable)
- Mapping of AI model's ranking to the bank's internal rating for a certain period, identifying accounts that needs monitoring
- Case study for certain borrowers (if applicable)

CRD Association's Transaction Model

- Key words: ADBI, Credit Scoring, Machine Learning
- Paper: https://www.adb.org/publications/credit-risk-database-sme-financial-inclusion

- Key words: HKMA, Alternative Credit Scoring, CRD
- Paper: https://www.hkma.gov.hk/media/eng/doc/key-functions/financial-infrastructure/alternative_credit_scoring.pdf

Key Takeaways

- Data exploration:
  - Transaction data: available within the bank, large scale, accurate
- Model selection:
  - Avoid black box
  - Avoid underfitting and overfitting (by cross validation)
- Model assessment: Interpretability, Accuracy (AUC), Stability (out-of-sample validation)→ Maintenance
- POC: easy way to test a model with your own data before actual deployment

CRD Association Japan

THANK YOU!

Q&A

Contact: Lan Nguyen
Email: nguyen@crd-office.net

CRD

Review of the approaches for a scoring model and the significance of CRD system

13 April 2023

CRD Association Japan and CRD Business Support

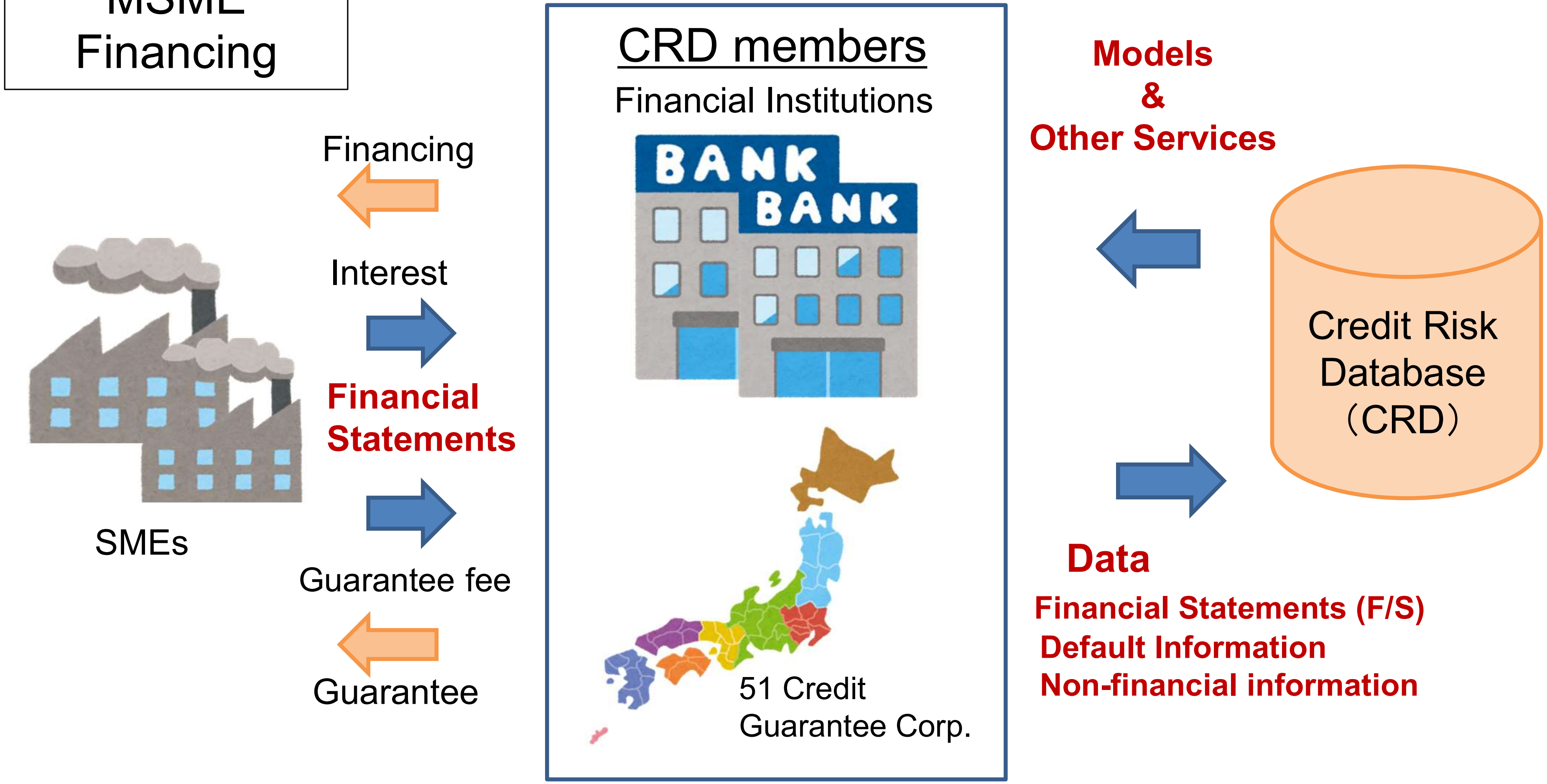
Key take away

- There are several types of scoring models currently prevailing such as (i) the expert judgement type, (ii) the credit bureau type, (iii) the bank in-house type, and (iv) the FS-CRD type. Each scoring model has its own characteristic, which arises from the availability and the selection of the data to be used.
- CRD type of scoring model uses anonymized and digitalized data comprising of (i) financial statements (FS) (ii) default and (iii) non financial statements of MSMEs using logistics regression methodology.
- CRD system established in 2001 has carried on a win-win link between banks and CRD in maintaining a large size of the database and the accurate / stable credit scoring model.
- CRD type of the scoring model is considered the best and the most skillful approach for analyzing on-going business performance of borrowers from financial statements with respect of stability, profitability, efficiency, and growth potential.
- CRD Association introduced an up-to-date scoring model using transaction data with the machine learning methodology. This can evaluate MSMEs without FS and monitor the performance with higher frequency.

CRD in Japan

Scheme of MSME Financing

Established in March 2001 as a non-profit and a membership organization



CRD members and data

【Membership Composition】

Credit guarantee corporations	51
Financial institutions (Government-affiliated & Private financial institutions)	95
Credit-rating agencies, etc.	16
Total	166
The governmental institutions (FSA, BOJ, SME Agency etc.)	4

【Accumulated data】

(Unit: 1,000)

	Number of debtor	Number of financial statements
Incorporated SMEs (default information)	2,970	26,340
Sole-proprietor SMEs (default information)	1,470	6,670

Note that both tables are created as of February 2023

Number of financial statements in CRD is more than 30 millions.

Basics of Credit Risk Scoring Model

What are the elements ?	**Target borrowers, whose credit risk to be assessed** : Consumers, A Sole Proprietorship, MSMEs (unlisted), Medium Sized Corporations (listed) and Large Corporations (listed),
	Available information / data
	An analytical methodology defining a model structure
Who owns and uses for what purpose?	**Credit Card Companies, and Mail Order / Large Retailers** — **Own Use**
	Banks and FIs / (Credit Guarantee Corps (CGCs)) — **Own Use**
	Credit Bureaus (CB)/(Credit Registry) — **Third Party Use**
	Credit Rating Agencies (CRA) — **Third Party Use**
	Credit Risk Database (CRD) — **Third Party Use**
What risk information to be provided ?	**Probability of Default (PD)**

Historical Overview (1)

1950s

- Billar Fair and Earl Isaac Model (Fair Isaac Corporation) started in 1956 for assessing consumer credit risk

1960s

- US Mail Order or Retail Companies for assessing consumers' credit risk

1970s-80s

- Credit Card Companies or Airliners' Card for assessing a risk of applicants
- Banks and FIs for assessing the credit risk of consumers' loans, mortgage loans and auto loans
- Banks and FIs for assessing the credit risk of corporations
- (Introduction of a statistical approach using Z Score and Standard Score)

Historical Overview (2)

1990s (Computerization)

- Banks and FIs introduced an internal credit rating system for extending loans (Introduction of Basel Accord)
- Banks and FIs started assessing a risk of small business loans (speedy credit process)
- Credit Bureaus (or a credit information company) provided to borrowers' credit information
- Credit Rating Agencies rated a bond issuer and provided a credit risk report to an investor
- Credit Registries, in the case they provides a credit report, conducted a scoring

2000s (Enhanced IT technology)

- Banks and FIs introduced quantitative risk management for an internal credit rating system for extending loans (Collapse of bubble economy in Japan and introduction of Basel II Accord)
- Establishment of CRD Japan with a large database and an accurate scoring model to member banks
- Some banks and FIs in Japan for scoring lending (not so successful Especially Shin Ginko Tokyo Ltd.)
- Banks and FIs applied IT technology for extending consumers' loans and mortgage loans
- Central Banks, who process variety of risk analysis or risk profiling from internal database

2010s Onwards Fintech, AI and DX

- Banks and FIs started using AI for consumer lending products
- Banks and FIs started account data and AI for small business loan

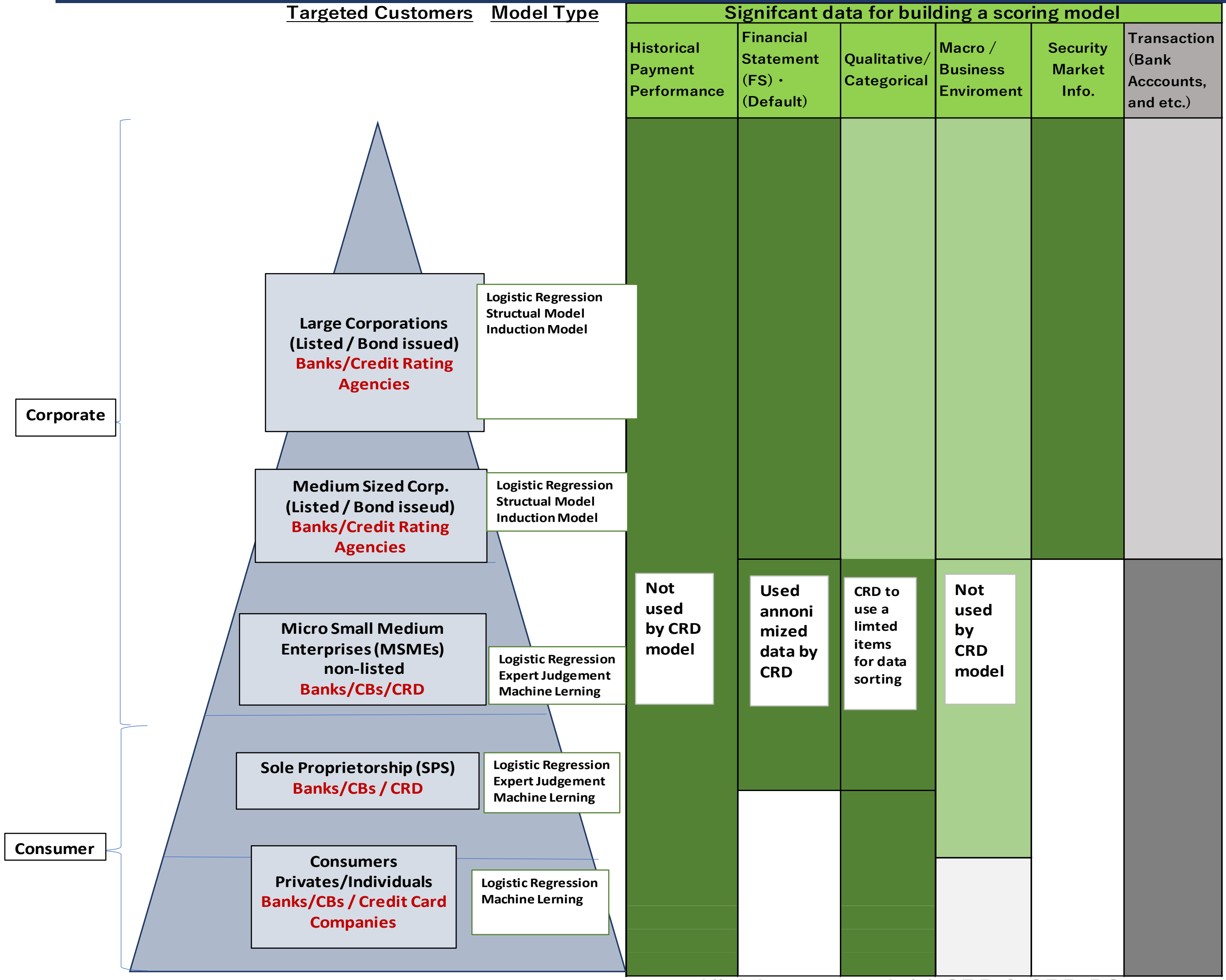
Credit Scoring Model Approaches and Methodology

B or W	Methodology	Name	Description/Characteristics
White Box	Using indexes for structuring a score table	Expert Judgement	· Indexes such as growth probability, profitability, effectivity, stableness and etc. · No good rationale for the selection of indexes and the weightage for he score table · Common and easy to introduce but non statistical
White Box	Statistical Model	Logistics regression	· Correlation between variety of explanatory variables and the probability of two objective variables. Commonly used by variety of users · Nature of a model differs depending on kinds and numbers of data to be used
		Linear discrimination	· Classical methodology for discriminating default and non-default · Explanatory and widely used before, but no more common due to inadequate accuracy
		Hazard analysis	· Used for imaging the term structure of default probability (ex. housing loan analysis) with long term data
White Box	Stochastic Model (options approach)	Structural model	· Measuring the asset value using the stock market price and seeking the level of insolvency · Eligible for listed companies with data available of the stock markets
		Induction model	· Measuring the credit risk using corporate bond price data · Eligible for corporate bond issued companies with data available of the bond markets
Grey Box	AI Score Model (Machine Learning)	Moderate degree (weak AI)	• Random Forest, Support Vector Machine (SVM)
Black Box		Intense degree (strong AI)	• Multilayer Neural Network, Deep Learning

White Box: (i)model logic is open and interpretive (ii) applicable for structural data

Black Box: (i) model logic is not open, and not totally interpretive (ii) applicable for structural data as well as non-structural data

Target Customers and the data for building a scoring model



Who owns the data? How to obtain?	
Historical payment performance	Banks and CGCs from in-house data or Credit Registry* Access to Credit Regisry by CB is conditional
Financial Statements Default data	Banks and CGCs directly from borrowers CRD from nenbers' banks and CGCs CBs' access is limited only from public sources, especially for non-listed MSMEs.
Qualitative / Categorical	Banks directly from borrowers through interviews. CBs may be from interviews and available public sources.
Macro / Business environment	Information provider, think tanks (Bloomberg, Thomson Reuter etc.)
Security Market information	Information provider, think tanks (Bloomberg, Thomson Reuter etc.)
Transaction data	Bank accounts information and etc.

Credit Registry (public entity)

A big presence in many of European(13), Asian(9) and Latin American(15) countries
—Germany in 1934, France in 1946, Spain in 1962, Italy in 1962, Belgium in 1967, Portugal in 1978, Austria in 1986

Credit Bureaus (private)

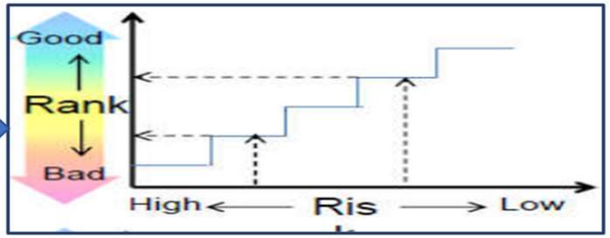
A big presence in US, UK and Japan
—Dun&Bradstreet (US, Established in1841)
TransUnion (US, Established in 1968)
Experian (UK, Established in 1970)
Tokyo Shoko Research (TSR) (Japan, Established in 1892)

- Essentially significant
- Generally significant
- Required
- Not so signficant or not available

Images and characteristics of scoring models

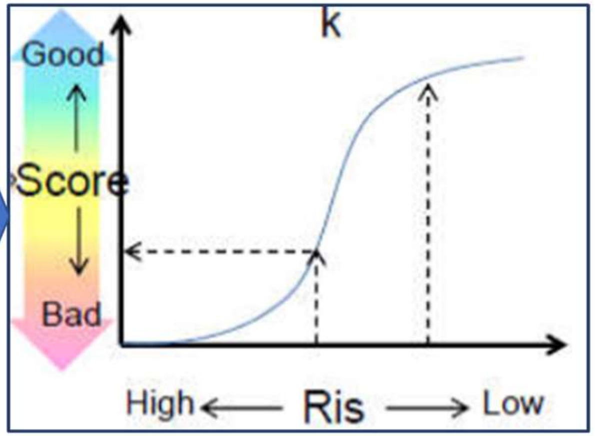
(Non-statistical)

Model Name	Owner	Usage	Data	Charactrer
(i) Expert Judgement Type Model	Banks	Corporates	a. Historical Payment b. Qualitative c. Macro/Business Env. d. Finanical Statements (FS)	**Dependenceon the individual skills:** Experts' subjective selection of variables Easy to introduce Limited to reflect the characteristics of the mother population of the scored samples

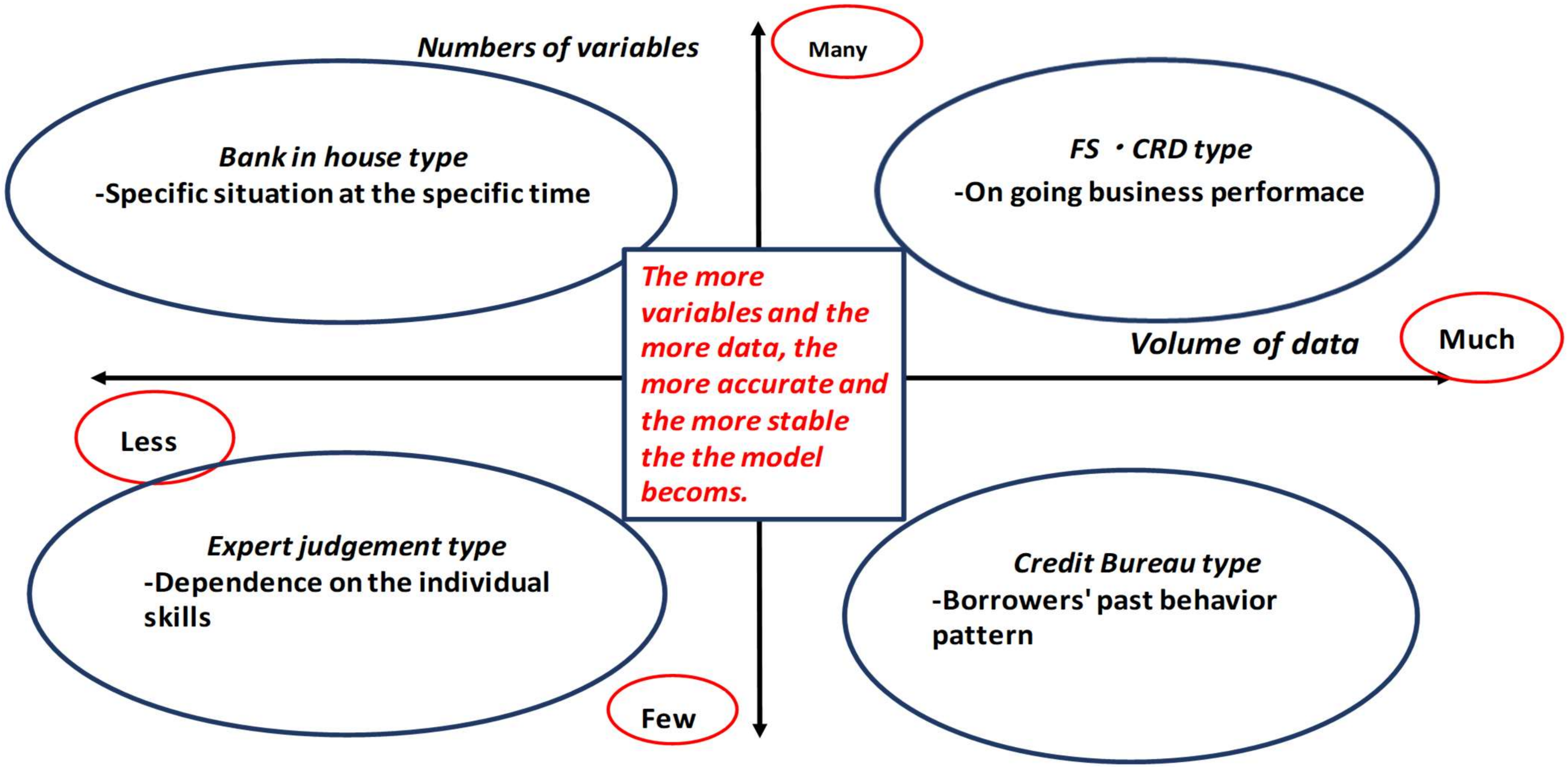


(Statistical: Logistic Regression)

Model Name	Owner	Usage	Data	Charactreristic
(ii) Credit Bureau Type	Credit Bureaus/Banks	Consumers/ Coprporates by CBs	a. Historical payment (main) b.Qualitative (sub) c. Financial statements (sub) with small numbers of variables	**Past Behaviro Patern (event driven):** Past loan performance data Able to construct with relatively small numbers of data items
(iii) Bank In-House Type	Banks	Corporates	a.Historical payment b. Financial statements with manay numbers of vairables, but small amount of data due to less availability of in-house data	**Specific situation at the sepcific times:** Past loan performance data Limited avaialbility of finaicial statement data
(iii) FS-type (CRD type)	CRD Japan	Corporates (SMEs)	a. FS (many numbers of items) b. Default c. Non-FS data	**On going business performance:** Large numbers and wide range of FS data required. 26-59 items from B/S and 9-26 items from P/L ,which creates 174 financial indexes as candidates (actual usage 20-30) for explanatory variables. The model evaluates the stability, the profitability, the efficiency, the growth potential and so on.



Significance of FS-CRD type scoring model (1)



Significance of FS-CRD type scoring model (2)

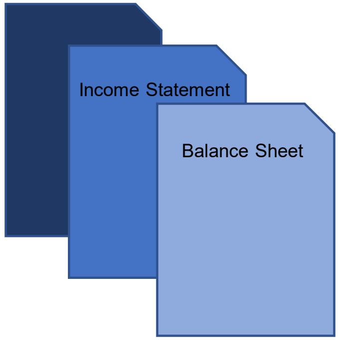
- Scoring model: assess the creditworthiness of borrowers by analyzing on-going business performance of borrowers from financial statements
  - Business performance: stability, profitability, efficiency, and growth potential
- In general, 20-30 financial indexes are used as explanatory variables for scoring models

Stability	Profitability	Efficiency	Growth Potential
Total Debt Ratio	Gross Profit Margin	Inventory Turnover Ratio	Revenue growth rate
Capital Adequacy Ratio	Operating Income Margin	Payable Turnover Ratio	Total Assets growth rate
Debt to Equity Ratio	Cost of Goods Sold Ratio	Capital Turnover Ratio	R&D investment
Interest expenses to interest bearing liability ratio	Operating Cash Flows Ratio	Receivable Turnover Days	Capital Investment
………	………	………	………

Scoring Models : difference in the countries

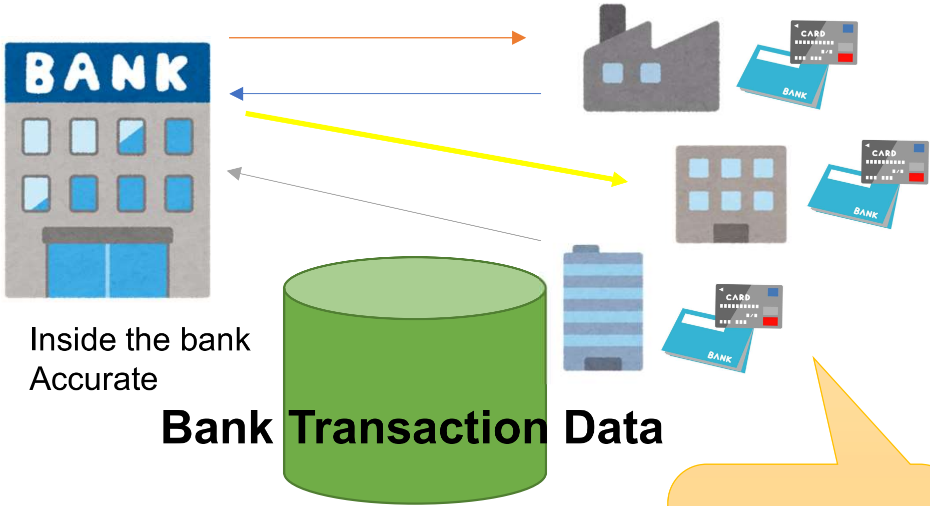
<table>
<tr><th></th><th>US, Europe and others</th><th>Japan</th><th>Philippines</th></tr>
<tr><td>Large Corporation
Middle Sized Corp.</td><td><Bank In-house Type>
Not sharing with other banks</td><td><Bank In-house Type>
Not sharing with other banks</td><td><Bank In-house Type>
Not sharing with other banks</td></tr>
<tr><td>MSMEs
Sole Propriatorship</td><td rowspan="2"><Credit Bureau Type>
Shared with banks
Ex. Dun&Bradstreet (US, Established in 1841), TransUnion (US, Established in 1968), Experian (UK, Established in 1970)</td><td><FS ・ CRD Type>
Annonimized data
Membership</td><td><Missing>
CRD under construction</td></tr>
<tr><td>Consumers (Card Loan Users)</td><td><Credit Bureau Type>
Shared with banks
Ex. Tokyo Shoko Research (Japan, Established in 1892)
Teikoku Databank (TDB) (Japan, Established in 1900)</td><td><Credit Bureau Type>
Shared with other banks
Ex. CIBI, CRIF PH. TransUnion PH</td></tr>
</table>

Use of alternative data approach for credit assessment



- Generally, once a year
- Sometimes, low quality
- Underdeveloped

Financial Statements Data



- Inside the bank
- Accurate

Bank Transaction Data

Monthly, weekly or daily data are available

- Increase the frequency and quality of credit assessment
- Broaden the opportunities for MSMEs financing

Two types of scoring models

		Traditional Model (FS・CRD type)	AI Model (Machine Learning Method)
Data		✓ Standardized Data---Financial Statements (FS) ✓ Frequency---Low (generally, once a year)	✓ Informative, but Complex Time-Series Data---Bank Accounts Data, information from Accounting Application on smartphone, SNS, etc.… ✓ Frequency---High
Outcome		✓ Longer term---Probability of Default (PD) within 1~3 years	✓ Short term---PD within 3months, 6months and so on
Usage	Internal Rating /Loan Examination	✓ Basement of evaluation--- Establishing own internal rating system based on traditional model	✓ Evaluation for MSMEs without FS (SMEs with underdeveloped accounting, low quality, etc.…)
	Validation	✓ Validation for Financial Institution's internal rating system by external scoring model	
	Monitoring		✓ High Frequency & targeted monitoring---Monitoring MSMEs effectively and raising an alarm promptly

Thank you

Jiro Tsunoda, Senior Advisor
jtsunoda@crd-office.net

CRD Association Japan and CRD Business Support Inc.