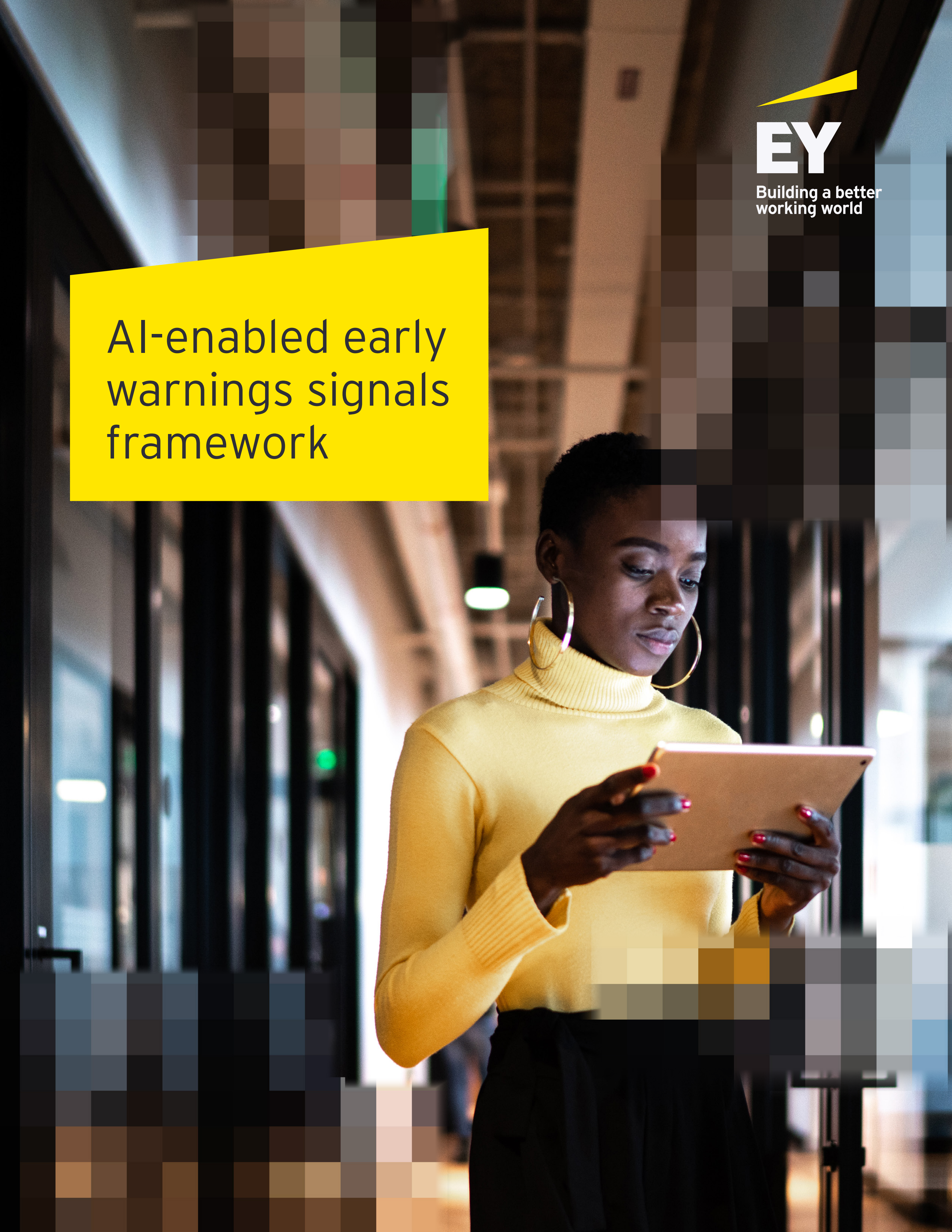
AI-enabled early warnings signals framework

Building a better working world



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Introduction

Motivation

As the global economy remains volatile and susceptible to economic shocks caused by supply chain disruptions, wars, the COVID-19 pandemic and other factors, risk management plays a crucial role in the stability of financial institutions.

Credit risk models are particularly vulnerable to large-scale volatility that can upend traditional frameworks for credit assessment. With a constantly changing environment, the characteristic data around credit risk is also evolving. While traditional risk modeling is gradually becoming forward looking, it tends to rely primarily on backward-looking data.

Generally, the data reflecting a present situation will not be incorporated into models until a data refresh occurs. Many legacy approaches taken to evaluate credit risk with commercial clients are limited by incomplete data with infrequent updates, poor alignment between risk assessments and front-line business operations, and an overemphasis on treating large credit facilities independently based on existing client relationships.

In recognition of these challenges, financial institutions have created early warning signals (EWS) frameworks that are supported by an appropriate IT and data infrastructure, allowing for the timely detection of increased credit risk in their aggregate portfolio as well as in portfolios, sub-portfolios, industries, geographies and individual exposures.

Organizations that successfully implement robust EWS frameworks have observed an immediate financial impact across three main aspects of the business: exposure reduction, new revenue and resource optimization. Overall, the estimated benefit based on top Canadian banks' benchmark ranges between CAD$6m and CAD$9m for the first year of operationalization, and subsequently higher returns.

Select observed benefits per year by a financial institution are outlined below:

CAD$1m – CAD$1.5m

credit loss provisions reduction for high-risk customers due to risk-mitigating action

CAD$2.5m – CAD$3m

new revenue generated from abridged annual review triggered for low-risk customers

CAD$3m – CAD$4m

cost savings from FTE esource optimization

What is EWS?

Early warning signals (EWS) are methods or key indicators that alert relationship managers and risk managers of potentially adversarial trends (e.g., client profile deterioration) that may impact an institution's economic health.

EWS frameworks have defined trigger levels driven by specified levels of credit risk appetite, strategy or policies. On identifying a trigger event at the level of an individual exposure, portfolio or borrower group, institutions undertake predefined measures and mitigation actions that may include applying more frequent monitoring of the obligors and, when necessary, placing them on a watch list.

Current landscape

Existing EWS frameworks for financial institutions are based on internally available and traditional data sources, such as demographic information, account and depository information, financial statements, or ratios for the counterparties, and select transactional data attributes.

Behavioural scorecards are also used to monitor borrowers' health. However, these scorecards are built on backward-looking data, which limits their potential. The frameworks are typically configured to capture expected downgrades in borrower risk rating or expected overdraft or delinquency behaviour by using classical statistical methods. Certain institutions also apply manual overrides to the framework outcomes to take into consideration data the model can't see, such as political uncertainty.

These insights are typically used across the following areas:

- Defining risk managers' actions, including point-in-time assignment of watchlist accounts
- Streamlining commercial obligors' annual reviews
- Assessing client creditworthiness
- Determining credit ratings for regulatory capital calculations

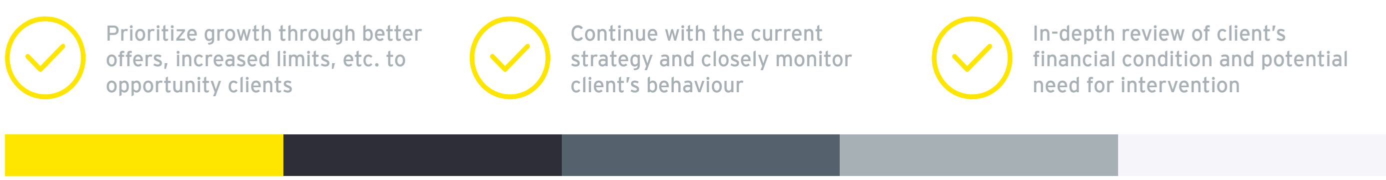
Today, financial institutions are facing unprecedented market volatility where the traditional EWS frameworks are becoming increasingly ineffective. There is now a heightened need for more dynamic predictive capabilities to bring timely, informative insights to leaders to support enterprise decisions in the face of uncertainty and enhance the risk management process.

Bridging the gap

An effective EWS framework bears impact on three main aspects of businesses: **exposure reduction, new revenue and resource optimization**. It allows decision-makers to track the client's financial condition and react appropriately.

Data-driven risk management actions

Figure 1: Business application of EWS framework output



The following characteristics must be carefully considered to build a reliable EWS framework for data-driven decision-making:

Early detection: Identifying and predicting leading indicators for detecting distress as compared to default events will enable institutions to have an earlier focus on possibly distressed clients. Such proactive risk management necessitates the use of unconventional internal and external data sources providing more relevant and higher frequency information.

This shift will enable relationship managers to maintain an active relationship with clients by focusing their attention on situations flagged by the framework and using their portfolio management time more effectively. In particular, risk is mitigated by engaging in more frequent evaluations beyond simply a traditional annual review.

Accuracy: An EWS system plays a pivotal part in effective risk management and must have a high detection ability. Often, the presence of many false negatives may result from various deficiencies in the overall framework.

One potential reason may be a reliance on limited source information, which may cause the organization to miss capturing the holistic view of a client.

Another driver of low accuracy may be inadequate segmentation of borrower population (i.e., disregarding borrower characteristics and considering all borrowers in the same way). Alternatively, despite relying on holistic data and appropriate segmentation, the organization may still not achieve adequate performance due to the underlying methodology if statistical methods lack the sophistication to model complex relationships between variables. To reach reliable outcomes, each aspect of the framework must be carefully evaluated for performance.

Text BoxExplainability: The rationale for recommendations established by EWS frameworks should be easy to understand, with reference to specific numerical data and industry and customer insights. A more transparent and explainable approach to understanding outputs leads to more confidence, uptake and acceptance when implementing these frameworks for consumption by stakeholders who might not have a granular understanding of how the systems work.

EY is currently spearheading the development of forward-looking and dynamic EWS frameworks for our financial institution clients. A comprehensive overview of the proposed methodology can be found in the subsequent sections.

Methodology

Data

Financial institutions can achieve a holistic view of the borrower by tapping into two major sources of data:

- Internal data, which encompasses information created and owned by the institution and already existing as part of the day-to-day operations
- External data, including third-party data or data an institution publishes to the public domain through official or non-official services

These sources can be further organized into structured data, stored in a pre-defined format, and unstructured data that's available in native format.

Financial institutions primarily use structured data sources that focus on lending information, internal risk assessments, general client data and overall client behaviour characteristics. These data sources tend to provide insight into financial patterns, which include financial statements, borrower risk ratings, other lending and mortgage statistics, delinquencies, etc.

However, there are certain limitations with using these sources alone. For example, data such as company financial statements could be up to a year old, which might not reflect the organization's current economic health. Hence, if a trigger event has occurred, there's a small window for precautionary action. In addition, some sources capture lagging signals (e.g., delinquency of payment).

Enriching the data with expansive sources increases the ability for early detection of credit quality deterioration. Data domains — including high-frequency transactional data, payroll data providing client liquidity information, external sources such as macroeconomic factors providing an economic overview of the client and the industry — can be used as additional inputs for enriching the signal. Sample relevant data points include overall credits, debit, interest rates, gross domestic product (GDP) ratio, unemployment rates, pay frequency and dollars, cash or credit card data, and snapshots of client relief.

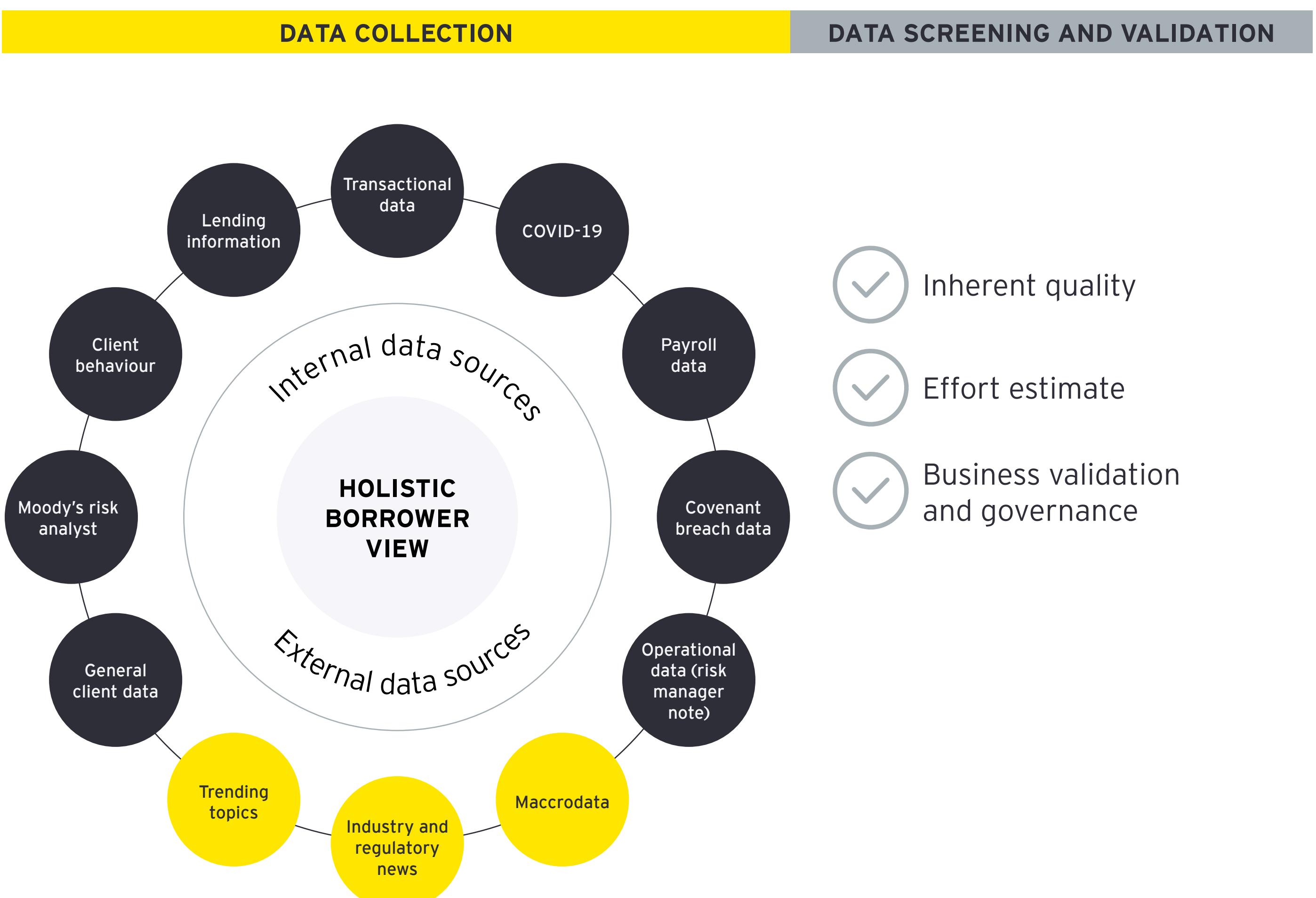
Incremental insights can be derived by extracting signals from unstructured data sources available internally, including annual review notes, operational data (e.g., agent notes, agent-client call interaction transcriptions), and external sources such as industry reports, financial news feeds and social media mentions. These externally available resources provide information on key industry drivers, growth forecasts and revenue forecast changes, industry- and client-level sentiment, trending topics and more. If handled appropriately to harness information from large volumes of textual data, these sources can have immense value in providing forward-looking indicators of customer profile deterioration .

Broadening data sources enables an institution to gauge the level of effort required for data governance. The trade-off between the value generated from a new data source and the corresponding governance effort must be carefully considered.

Data governance effort assessments must be performed in a structured way, addressing key data management steps in collaboration with the institution's data privacy and data governance functions. The use of internal data and published external data sources, such as industry reports, typically requires limited data governance effort, with only a few steps required, such as providing documentation and attestation.

In contrast, open-source external data sources, such as financial news or social media interactions, necessitate higher effort, with the need for new controls or considerations. Since the data sources are varied and the information can provide tremendous value to the client, governance frameworks play a crucial role in the overall data aggregation and handling processes.

Figure 2: Internal and external data collection and review



Advanced modeling framework

Two major components, the success criteria and target definition, are crucial in setting up an appropriate EWS framework to fit the organization's needs.

These components are defined by conducting a thorough current-state assessment, data availability and exploration in partnership with the business's stakeholders.

The success criteria are established in alignment with the risk team, where they are measurable and rooted in a strong understanding of business objectives and limitations of the existing EWS framework (e.g., reduction in false positives).

The targets are defined based on subject matter expert input and the data exploration performed on internal and external data sources. Some examples of target variables include overdraft and liquidity. A good target is related to client behaviour prior to an adverse event and can detect credit deterioration as early as possible. Defining these two parameters in advance sets up the objective of the iterative modeling process, including design and development of the set of models followed by an optimal model selection approach in a seamless manner.

As a part of the modeling framework, effective feature engineering and subsequent feature selection play a significant role in deriving the most predictive explanatory features and preventing algorithmic bias. The key focus for feature engineering is to derive risk indicators from raw data in conjunction with domain knowledge. Typical approaches used for structured data include variable encoding, statistical metrics for numerical datasets, numerical transformations and variable change over time, among others. Unstructured data such as text requires the application of natural language processing (NLP) techniques to perform automated data processing and information extraction, resulting in a selective curation of NLP features.

An NLP pipeline for feature extraction includes modules for text normalization, parsing and so forth, followed by NLP modeling, such as sentiment analysis and topic modeling. The NLP pipeline should be developed as an additive and modular component, which allows a financial institution to assess value-add prior to implementing or deploying the component for risk management purposes.

The consolidated dataset comprises features derived from the structured and unstructured data sources, such as NLP-derived features from text data. The feature selection process is performed for all candidate target variables.

Based on the defined success criteria, target variables and the feature sets, the model development and the selection processes are initiated. Multiple instances of the model are assembled in parallel using different feature sets and machine learning (ML) methodologies, and various performance metrics are evaluated to compare candidate models and select the best-performing model.

The model outputs are then evaluated against the selected success criteria. If the model passes the success criteria, the next stage of the framework is initiated. However, if the model fails, thn the selection of target variables will be reviewed. This iterative process makes the modeling framework robust, allowing for evaluations to be performed at key stages in the process, giving decision-makers an enhanced risk management process. With the adoption of advanced ML techniques, there can be a significant lift in performance, and validation considerations, such as model-overfitting and model stability, become important to the overall EWS framework.

Proposed approach

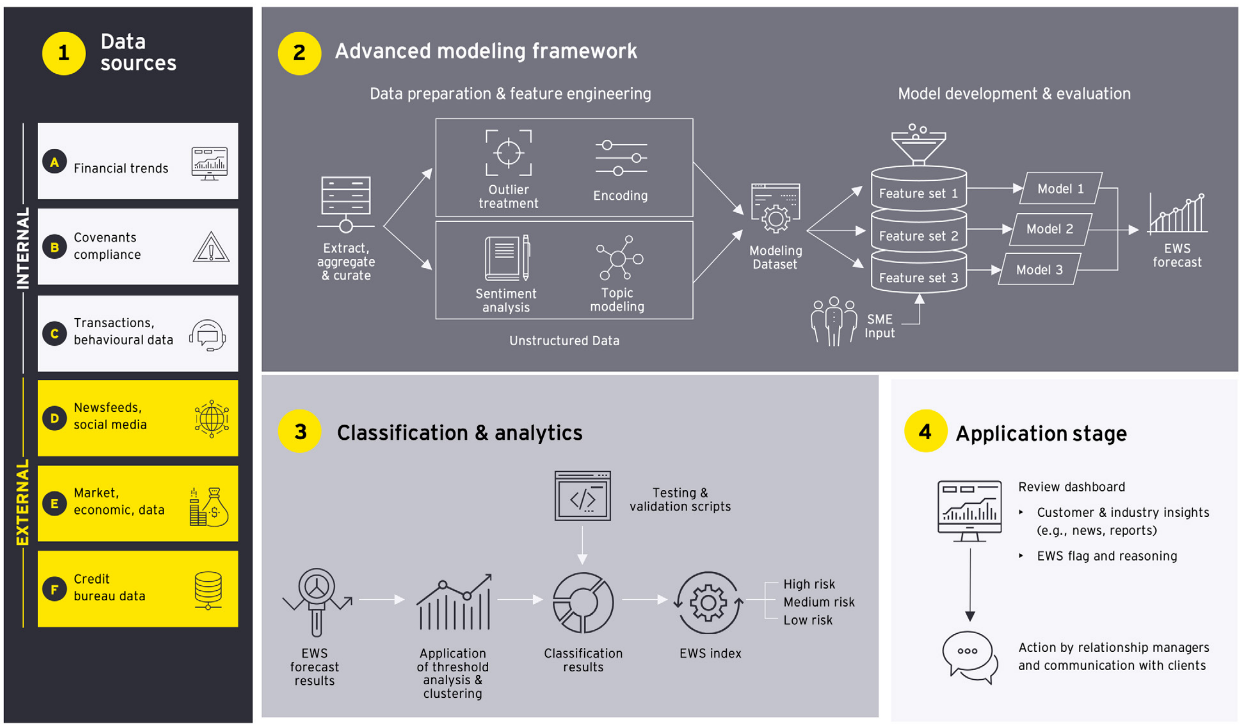
The model output (i.e., the predicted EWS forecast) is applied in the classification and analytics step that identifies the optimal cutoff for serving business needs by classifying customers into different risk categories.

The main objective of classification and analytics is to help relationship managers with appropriate action planning (e.g., identifying the customer group requiring attention and devising corrective action plans for each group of customers based on their characteristics and behaviours). An appropriate cutoff can be determined by first analyzing the distribution of agreed metrics across client portfolios and then applying the business capacity or risk appetite as constraints and classifying the client population.

Other methods, such as custom decision matrices, logistic regression, decision trees and others, may be used for classification in cases where multiple target variables are being used in the EWS framework. The classification can be further refined based on characteristics, such as industry or company size.

The final stage is to perform score reasoning and derive scenarios based on the classification analysis, where the score reasoning is determined by understanding the top explanatory variables that contribute to the model's decision. These explanatory variables are consolidated into higher-level drivers based on similarity. This analysis and subsequent visualization of the drivers add interpretability to the model score, which is ultimately used to assign corrective action plans to customers in each category.

Figure 3: Proposed end-to-end EWS solution



Benefits

A dynamic and proactive EWS framework can drive immense value for a financial institution by enabling effective risk management and data-driven decision-making by management.

Primary applications of EWS for business use are as follows:

- Projected credit losses (PCL) reduction - Identify issues early and flag commercial obligor deterioration, helping bankers better serve clients and limit adverse impacts on PCLs.
- Dynamic assignment of annual review intensity - Use the early warning signal and existing bank capabilities to develop a dynamic assignment of annual review intensity based on performance categorization that optimizes both risk and full-time equivalent effort.
- Risk-specific product offerings - Use the early warning signal and existing bank capabilities to anticipate risk management and product needs of commercial obligors.

Case Study

A financial institution was interested in improving its EWS framework for its commercial portfolio. The existing framework was extremely sensitive to exposure changes, had a complex trigger mechanism lacking transparency, and resulted in a high false-positive rate.

EY teams assisted the bank with a two-fold objective of proactively detecting borrower credit quality deterioration or improvement, particularly in higher-exposure categories, and supporting user consumption of the output. The project's scope was to develop a challenger surveillance flag with the ability to support current client risk profile reviews. This scope was also intended to serve as a basis for operationalizing the output in a phased approach by initially incorporating the result as an additional layer to the current watch list process, and later developing an enhanced watch list process to replace the existing approach.

In our assessment of the bank's existing monitoring approach, we identified the use of limited data sources and discovered that the model depended on input information that lagged in nature. A thorough data discovery process was conducted that concluded in identifying additional data sources that had a higher frequency of updates, better aligning with changes to the borrower's credit position. These sources also represented a more comprehensive external view of the client encompassing industry reports, regulatory news, industry news and macroeconomic conditions of the industry, among others.

Initial dataset screening was performed and robust data ingestion and data-cleaning pipelines were developed to embed appropriate data quality. To achieve feasibility and governance requirements for using selected internal and external sources, we engaged with subject matter experts from the bank.

The data was consolidated into different modules based on product characteristics and data availability, and each module had a unique target variable aimed at detecting credit deterioration as early as possible. Sample target variables considered included balance-to-limit and balance volatility ratios, insufficient fund count and more.

The multi-step feature preprocessing, reduction and selection procedures relying on advanced methods were used to identify the most predictive explanatory features and prevent algorithmic bias. For example, NLP techniques were used to extract valuable information from industry reports, including industry outlook sentiment polarity, and historical and forecasted values from key industry statistics. Various newly identified data source-based signals demonstrated high predictive power, such as macroeconomic features, including unemployment rate and long-term interest rate. Various candidate models were developed and evaluated against the existing methodology used as a baseline. The developed approaches varied in complexity and feature sets involved.

The model performance was evaluated using metrics such as the Gini accuracy ratio and F1 score. The challenger surveillance flag was provisioned to the relationship managers using a custom-developed dashboard that also included outcome explainability and other NLP-derived industry insight metrics.

The direct impact of the model results was calculated by analyzing the detection rates for default on a historical time period. The improved detection rate was expected to result in an approximately CAD$50m potential annual loss reduction.

Conclusion

Given the dynamic and fast-changing market conditions evidenced by historical events, robust EWS frameworks are crucial for anticipating the impact on customer performance and resilience, thereby allowing for more proactive and effective customer solutions.

We've discussed all aspects of the EWS ecosystem, starting from expanding the data leverage, using advanced AI approaches for better insights, and embedding the data-driven results into business operations and risk management actions. There is an enormous potential for expanding such EWS frameworks and their components to other sectors and expanding the scope from commercial to retail portfolios.

Additionally, the client-level insights can be applied to activate opportunities beyond risk management, including marketing effectiveness through timely customer-centric offerings, operational savings through NLP and AI-enabled automation, and an improved client experience based on a 360-degree understanding of customers and their needs.

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EY exists to build a better working world, helping to create long-term value for clients, people and society and build trust in the capital markets.

Enabled by data and technology, diverse EY teams in over 150 countries provide trust through assurance and help clients grow, transform and operate.

Working across assurance, consulting, law, strategy, tax and transactions, EY teams ask better questions to find new answers for the complex issues facing our world today.

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