CEROP: Cross-Border Enterprise Risk & Operations Predictor
Week 2 : Frame the Problem and Proposal

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Frame the Problem

The objective is to minimise the business and monetary losses faced by enterprises when they enter into contracts and provide credit to cross border partners when they have no visibility of two risks that often mutually compound, namely financial distress and failure to deliver products in the supply chain. Similar measures of supplier survival or lack thereof are already available as commercial products on third-party risk platforms, like Dun & Bradstreet's Dun & Bradstreet Supplier Evaluation Risk Rating, which rates how likely a supplier will cease operations within 12 months. That proves there's a business case. The key contribution we make is that we integrate the financial-risk view and the operations-risk view (late delivery) into one system, taking macroeconomic context into consideration, rather than considering the two views separately.

The idea would be for it to be a valuation tool for risk, procurement and finance teams to use as a decision support tool prior to extending credit, renewing contracts or examining supplier relationships. The outputs from the financial-distress model and the delivery-risk model will be distinct, and appear in a way that mirrors the way different risk-scoring platforms do when providing information to decision-makers (Censinet, Inc., 2025). These results would further support the ability for human decision making.

There are already some commercial platforms that tackle aspects of this problem. Dun & Bradstreet's Supplier Evaluation Risk (SER) Rating assigns a score of 1 to 9 to suppliers based upon a combination of their payment behavior, net worth, number of employees and legal filings, and Dun & Bradstreet's PAYDEX Score measures supplier payment behavior (Dun & Bradstreet, 2026). Moody's (formerly Bureau van Dijk/Orbis) provides supplier risk scorecards

based on geographic location, ownership, financial stability and regulatory risk (Moody's, n.d.). Industry guidance further includes common specific practices like security questionnaires, ongoing monitoring, and Likelihood x Impact scoring models (Censinet, Inc., 2025). The common feature of all these tools is that they are proprietary, subscription-based, only downloaded periodically as opposed to continuously, and do not directly incorporate macro-economic indicators into the company-level score - directly what our system aims for.

This is a supervised (batch/offline) binary classification problem. Both target data sets have a historical label for each data set: bankruptcy status (financial layer) and late delivery status (operations layer). Training will then be done with fixed/versioned offline datasets, as the course textbook allows in the supervised classification lifecycle.

Only accuracy is not suitable for use in the financial-risk layer due to Taiwan's Bankruptcy is highly imbalanced (about 3.23% positive class). Instead, the precision, recall, f1-score and auc-roc values will be used. To accurately evaluate the capabilities of the models, this approach was followed very similar to the ones used by the dataset's originators who assessed models not just in terms of accuracy, but also in terms of Type I and II error rates, as well as ROC curves (Liang et al., 2016). In the case of an operations-risk layer, similar publications using the same DataCo dataset create similar accuracy, F1-scores, and AUC-ROC scores as their standard metrics (Ahmed et al., 2025).

Yes, yes with a weighting rationale. A Type I error (incorrectly determining that a company that is going bankrupt is 'safe') was found to be more expensive than a Type II error (incorrectly determining that a company that is 'safe' is going bankrupt) in the original bankruptcy study (Liang et al., 2016). This ties into our business goal – the cost of missing a real

high-risk cross border partner is greater than the cost of a manual review that's not required. For candidate models, recall will therefore be given more weight than precision.

According to the original study by Liang et al. (2016), Random Forest achieved 87% accuracy for the financial distress layer, while Logistic Regression and Linear Discriminant Analysis had accuracies of 69% and 50%, respectively. Other more recent studies that apply other imbalance handling methods with the identical dataset achieve performance levels of 0.93-0.94 for accuracy, F1 and AUC. Student goal: 85% or better accuracy and 80 % or better recall. The accuracy for the operations-risk layer varies from 90% to 96% depending on the model (published : XGBoost and hybrid SOM+ANN deep learning) with a comparable framework having an F1 of 0.91 and AUC-ROC of 0.943, when applied to the DataCo dataset. Standard, non-deep learning ensemblest methods and algorithms covered in this course, can achieve a minimum target of 85% or greater accuracy/F1.

Yes. Such machine-learning approaches have been applied in corporate bankruptcy and also in predicting delivery risk in the application of material to the supply chain. The related research have applied models like Random Forest, XGBoost and SMOTE to address the issues of class imbalance; these models and techniques can be applicable to this project (Liang et al., 2016; Ahmed et al., 2025). The DataCo dataset has also been used in different investigations comparing the different approaches employed, thus giving a valid point of reference for the selection and validation of the models (Constante, 2019). These existing methods will enable the team to build off already existing methods rather than develop it from scratch.

Yes and that's a definite advantage here. Arthunya possesses international financial services and FinTech experience, and has previously researched vendor & third-party risk detection frameworks. That background affects how you read the particular features; what

financial ratios are really red flags; and whether output of the model is statistically sound but may not be true.

Traditionally, a financial or credit analyst solves a financial statement by manually analysing the ratio analysis which includes liquidity, solvency and profitability ratios, a red flag checklist covering late payments, litigation history, ownership changes and third party credit reports from Dun & Bradstreet for example like PAYDEX and SER ratings (Dun & Bradstreet, 2026). An analyst would follow physical shipment methods and the delays they would encounter in the past along with geographical risks for supply chain risk. This is a manual process, prone to errors, and time consuming, not scalable for a comprehensive vendor portfolio across the borders. That's what we need to fix our system.

Even though built from enterprise data from the same market in Taiwan, 1999–2009, the financial ratio patterns found on the group of Taiwanese companies seem to extend to the behaviour of enterprises more widely across the boundaries of the country.

Though based on one company's logistics network, these patterns of late delivery (2015-2019) in the DataCo dataset are representative of general patterns of operational risk.

Even though measured at a global macro level, the Global Supply Chain Pressure Index is measurably correlated with the company level operational risk, statistically speaking. This enhancement applies to only the operations-risk layer (DataCo) as there isn't a date field for the records in the Taiwanese Bankruptcy dataset needed to merge with a macro-index assigned on a monthly basis.

The aim of this course is to provide a support to real-time deployment, and there is no requirement that the model trained in real-time time. There is an acceptable alternative, namely a batch-trained, periodically re-trained model to simulate a real-time monitoring system.

Assumption verification will occur in Week 3 (Get and Explore the Data) through correlation analysis between GSCPI values and financial/operational risk labels, and through descriptive comparison of feature distributions across the two datasets to check for structural inconsistency. Any assumption that fails verification (e.g., no measurable GSCPI correlation) will be documented and the modeling approach adjusted accordingly rather than silently discarded.

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Proposal

Selected Problem Statement

If a firm is faced with foreign suppliers, they may make decisions without fully appreciating the risks they are facing.A firm that deals with foreign suppliers may make a decision without having a complete appreciation of the risks that it is facing. Financial health is typically measured in the past using accounting information and delivery performance is measured separately using shipping / logistics information. Evaluating risks on an individual basis can be more difficult when it comes to detecting if financial problems of a partner could be linked to late deliveries or other operational concerns. Obviously, it's a legitimate business need, as seen in the commercial resources like Dun & Bradstreet's Supplier Evaluation Risk Rating and Moody's supplier risk scorecards that tackle portions of the issue. Typically, these tools examine financial or operational data in isolation from each other and do not provide a consolidated financial and operational risk analysis.

Significance and Industrial Impact

There is a need for enterprises to ‘fill the gap' at this intersection for enterprise sustainability and supply chain resilience. Disproportionate downstream consequences for the

affected companies can occur from the failure of a single node in the cross border supply chain because of substantial financial distress of that supplier coupled with reported volatility in shipments, which is why it is possible to have a widespread upstream impact on global shipping rivals, particularly manufacturing companies, in the wake of that failure, as noted by the Fed Reserve Bank of New York in its Global Supply Chain Pressure Index (Global SCPI), that it maintains and updates on a regular basis(n.d.). Academic work for both sides of the problem continues with peer-review academic publications in this domain. This project combines macro-economic pressure signals with firm-specific finance and operations metrics, and takes the assessment process from post the event reporting and analysis to early, evidence-based risk identification.

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The challenge of CEROP is solved with a dual-layer supervised classification architecture that is complemented by a macroeconomic signal layer, and is met at the end by the single output of the decision-support.

Layer 1 - Financial Distress Classification.

This layer will be created based on the Taiwanese Bankruptcy Prediction Dataset provided by UCI Machine Learning Repository, which includes 6,819 corporations and 95 financial ratio features. Ensemble classifiers like Random Forest and gradient-boosted methods (such as XGBoost) are well suited classifiers as they performed well on this very dataset in previous research and as they were shown to be well suited to the problem of extreme class imbalance on this dataset (about 3.23% positive class, which is common in most classification tasks). The final classification model to be used will not be determined a priori, but rather during the Week 5 model-comparison activity.

Layer 2 - Supply Chain Operations Risk Classification.

This layer will draw on the DataCo Smart Supply Chain dataset (2025) (180,519 records 53 features with a built-in label of delivery or logistics delay risk - Ahmed et al., 2025) and classify the probability of delivery or logistics delay. This is a reasonable performance benchmark for this layer as comparable published works have reported achieving results between approximately 90% using standard ensemble methods and in excess of 96% using hybrid deep learning methods (Liang et al., 2016; Ahmed et al., 2025).

Data Enrichment Layer - Macroeconomic Pressure.

Both levels of classification will be supplemented by theGlobal Supply Chain Pressure Index (n.d.), which is measured monthly by theFederal Reserve Bank of New York. When combined with operational data, these frameworks have demonstrated the meaningfulness of this macro-feature for supporting delivery-risk prediction.

The output of both layers will be consolidated into a global risk report that will provide a bigger picture of global vendor's financial risk and operational profile for these visual risk scorecards, enabling the risk and procurement teams to see the global vendor's profile together prior to extending credit or renewing a contract, or approving a new vendor. That would end the manual and silo approach to review which is the norm now.

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