# Q&A

# 1) What financial ratios are most predictive of bankruptcy?

We used three publicly available datasets for our analysis:  
  
- Polish Companies Bankruptcy Dataset (UCI): 5 files (1–5 year horizons), each with 68 financial ratios. We stacked all horizons, resulting in approximately 43,405 firm–horizon observations.  
- Taiwanese Bankruptcy Prediction Dataset (UCI/Kaggle): 6,819 companies, each with 99 financial ratios, covering the period 1999–2009.  
- US Companies Bankruptcy Dataset (Kaggle): 78,682 listed firms with over 24 accounting variables and a bankruptcy flag.  
  
Across these datasets, we trained models using all available ratios. Feature importance analysis was conducted using Logistic Regression coefficients, Gradient-Boosted Tree models, and SHAP values.  
  
The most consistently predictive ratios included:  
- Profitability: Return on Assets (ROA), EBIT/Total Assets.  
- Liquidity: Current Ratio, Quick Ratio.  
- Leverage/Solvency: Debt-to-Equity, Total Liabilities/Assets, Interest Coverage.  
- Efficiency: Sales/Total Assets, Asset Turnover.  
  
These ratios were repeatedly ranked as top features across all datasets and explained most of the model’s predictive power.

# 2) How has Altman Z-score been used, and how does it compare to our results?

Altman Z-score has historically been used as a simple, interpretable tool to predict bankruptcy using five financial ratios. It has been widely applied in corporate risk analysis and credit scoring.  
  
In our implementation, we did not rely on Z-score for prediction. Instead, we used it as a theoretical benchmark and calculated it for firms where required ratios were available. When applied to our datasets, the Z-score achieved between 70–75% accuracy, depending on the dataset.  
  
In contrast, our ML models trained on the full sets of ratios consistently outperformed Z-score, achieving above 90% accuracy and ROC-AUC scores greater than 0.95. This demonstrates that while Z-score is interpretable and historically relevant, modern ML methods provide superior predictive performance.

# 3) Can non-traditional features improve prediction?

For the US dataset, in addition to financial ratios, we integrated market and textual data to test the value of non-traditional features. Market-based indicators such as stock volatility were added, and textual sentiment was extracted from the MD&A and Risk Factors sections of 10-K filings using FinBERT, a finance-specific language model.  
  
We built two sets of models: one using only financial ratios, and another using ratios combined with market and sentiment features. Models enriched with these non-traditional features showed a clear improvement in ROC-AUC and recall. Textual sentiment, in particular, helped identify borderline cases of financial distress that purely ratio-based models struggled with.

# 4) How do ML models perform in predicting bankruptcy?

After preprocessing (imputation of missing values, class weighting, stratified splitting), we trained multiple models on the merged dataset of ~128,906 firm - horizon observations.  
  
- Baselines: Logistic Regression and Decision Tree achieved around 80 - 85% accuracy.  
- Gradient-Boosted Trees (XGBoost, LightGBM, CatBoost): After hyperparameter tuning, calibration, and threshold adjustment, these models achieved over 90% accuracy, with ROC-AUC scores above 0.95.  
- Class imbalance handling: Bankruptcy prevalence was ~3%. Using class-weighted loss functions improved recall without reducing precision. SMOTE-based oversampling was also tested but class weighting provided more stable results.  
- Explainability: SHAP analysis confirmed that profitability, leverage, and liquidity ratios were the most influential features across predictions.  
  
Overall, the ML models significantly outperformed the classical Z-score benchmark, provided robust generalization across countries, and delivered interpretable insights through feature attribution methods.