TRADETEQ AI
CREDIT RISK MODELS

February 2021

OUR GLOBAL AI COLLABORATION NETWORK

Creative Destruction Lab, HEC Montreal

2018
Graduated from the AI stream of the leading Canadian start-up accelerator

Oxford University

2019-2021
Supervising student research projects at the Department of Computer Science

Wroclaw University

2019
Financing a project on advanced transaction scoring models. Retaining a team of 6 professors/graduate students to research application of graph machine learning on Tradeteq data

Singapore Management University/MAS/IBM

2020-2021
A collaboration of Tradeteq and SMU awarded SGD1.5m Artificial Intelligence and Data Analytics grant by the Monetary Authority of Singapore and joined the IBM Q Network

OUR AWARDS

UK FinTech Awards 2020:
Innovator of the Year

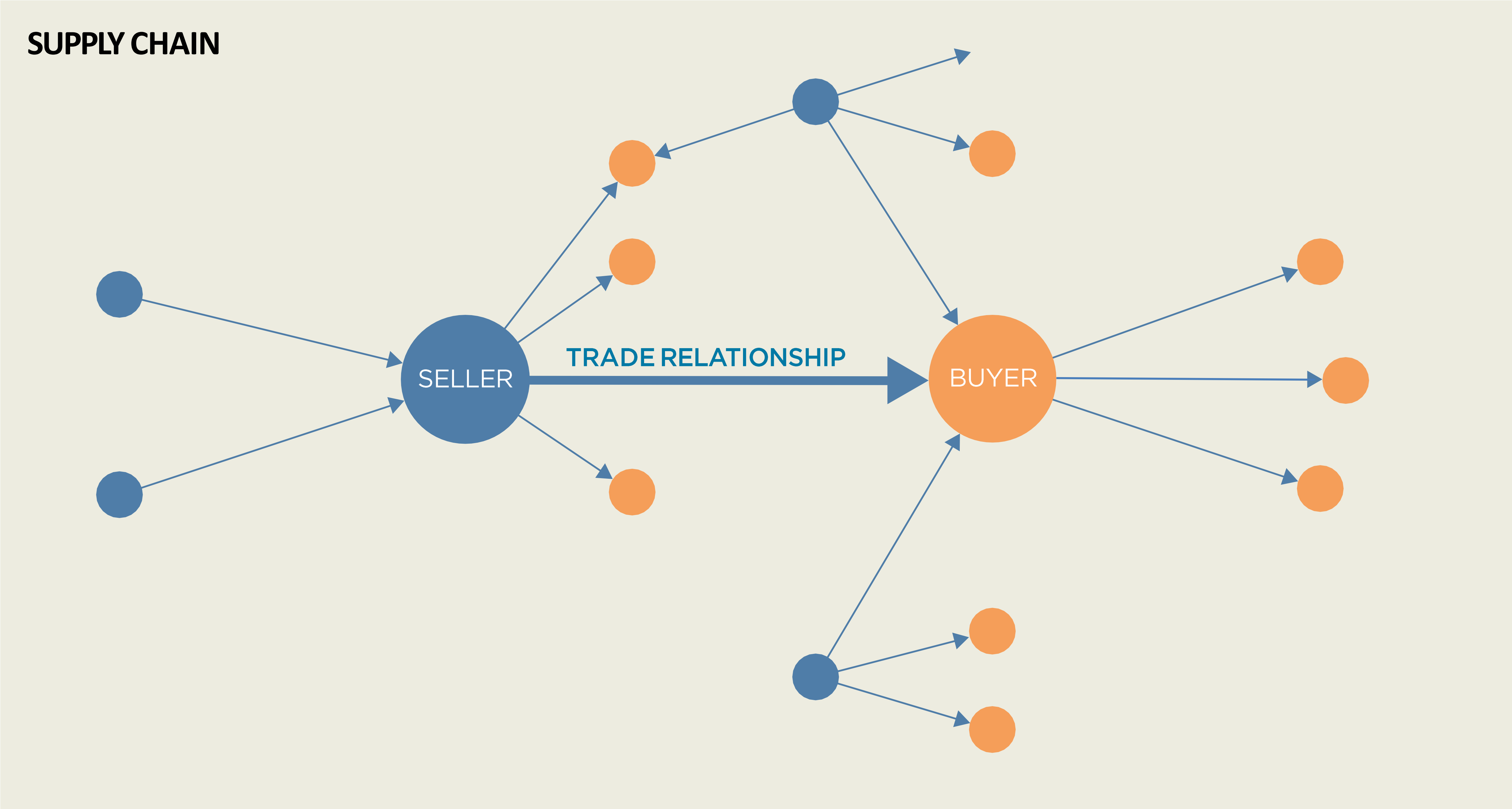
Risk Markets Technology Awards 2021:
Best use of machine learning/AI

CREDIT RISK ON THE SUPPLY CHAIN

Traditional credit analysis relies on debtor features to assess creditworthiness.

Trade relationship information is often more reliable, more granular, and always more timely than company information. A flow of frequent and repetitive transactions enables the application of powerful machine learning techniques to transaction risk assessment.

Tradeteq is providing its clients with two distinct credit models: a *company model* that produces a score for the likelihood of company insolvency/administration, and a *transaction model* that assesses risks for each trade finance transaction.

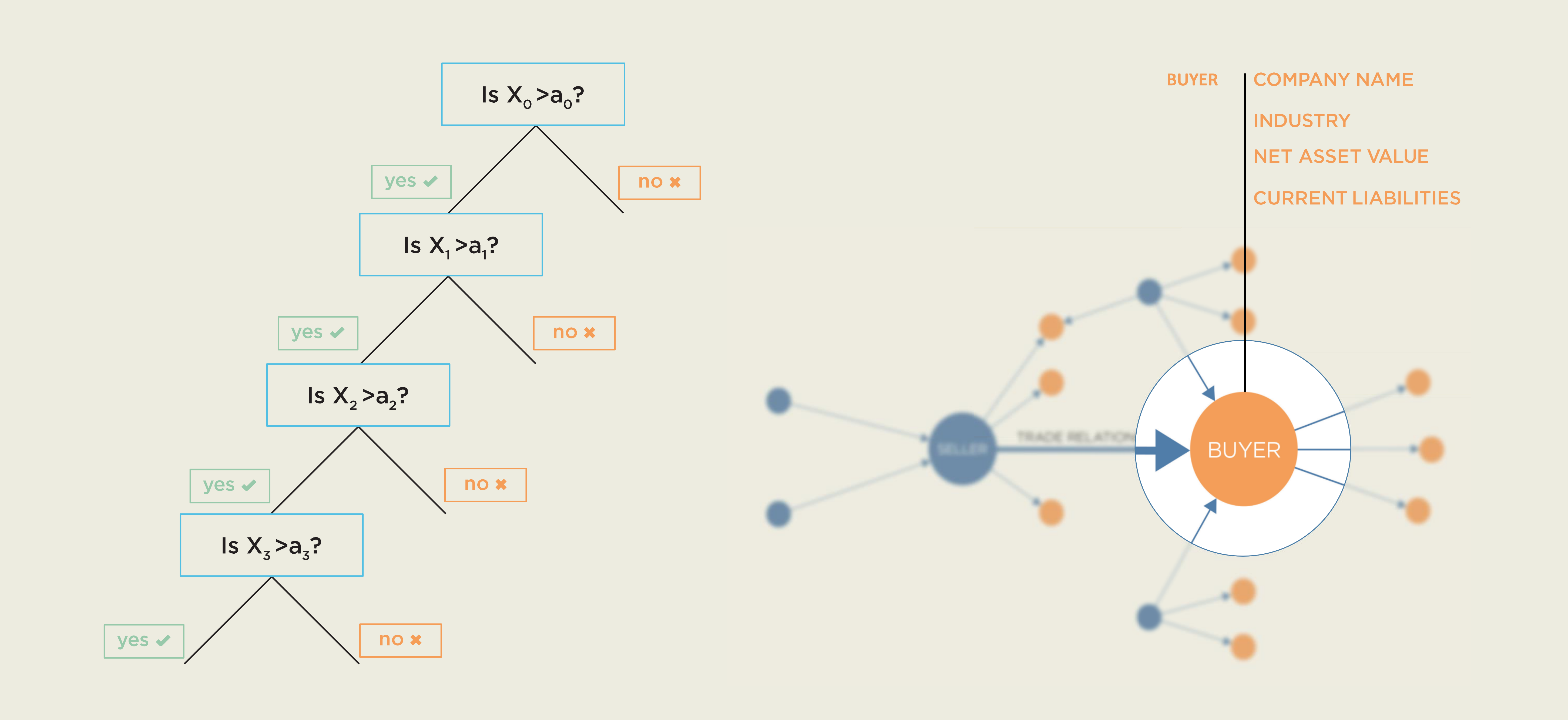


THE TRADITIONAL APPROACHES

Traditional credit analysis is focusing on the debtor alone, not on their wider trade relationships

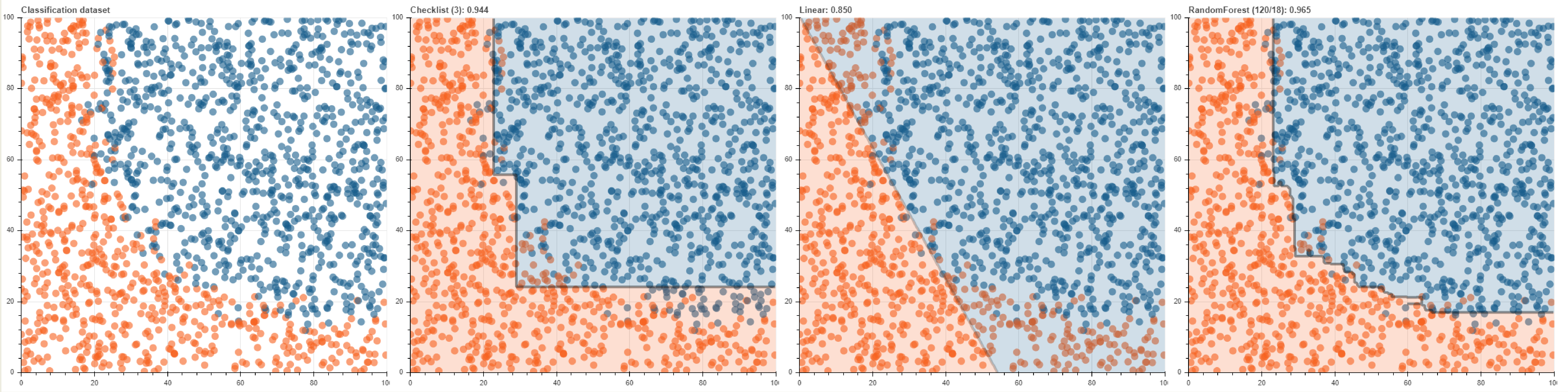
The most ubiquitous credit risk decision making process is the checklist – basically, a very unbalanced decision tree. It is a very restricted risk model.

Linear credit scoring, e.g. Z-scoring is a bit more powerful but still sub-optimal as it over-relies on accounting data.



BENEFITS OF MORE COMPLEX MODELS

Checklists and linear models may fail to capture very basic patterns in data



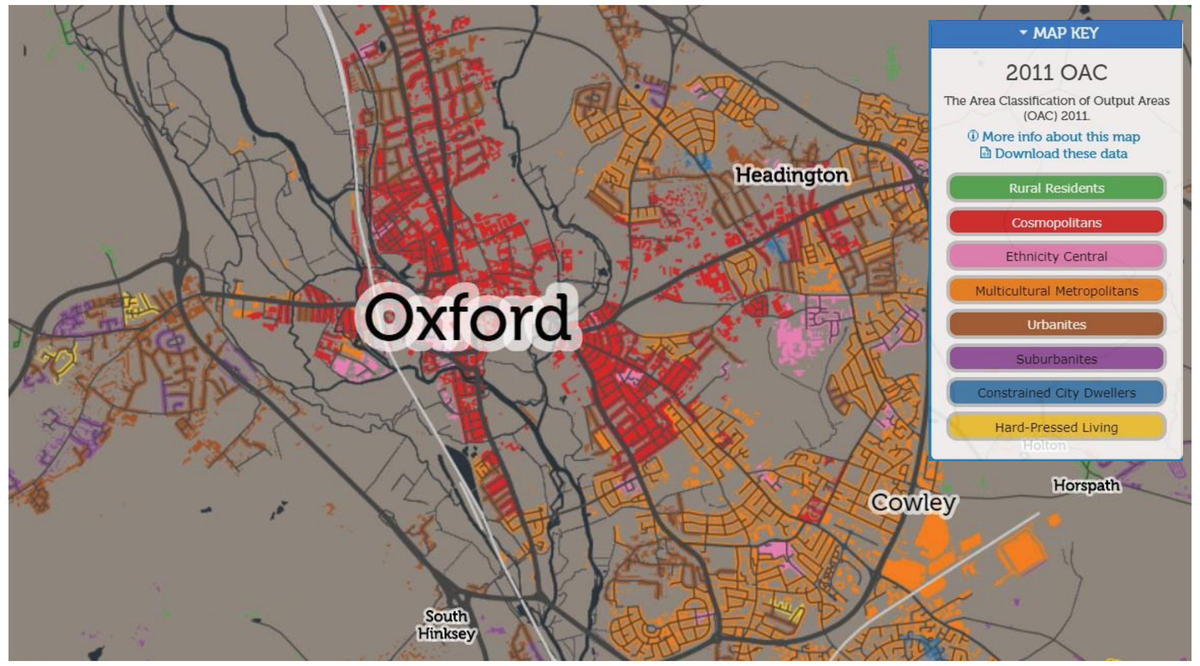
Source: Tradeteq. Simulated data for illustration purposes only

IMPROVING COMPANY CREDIT SCORING THROUGH MORE DATA AND BETTER MODELS

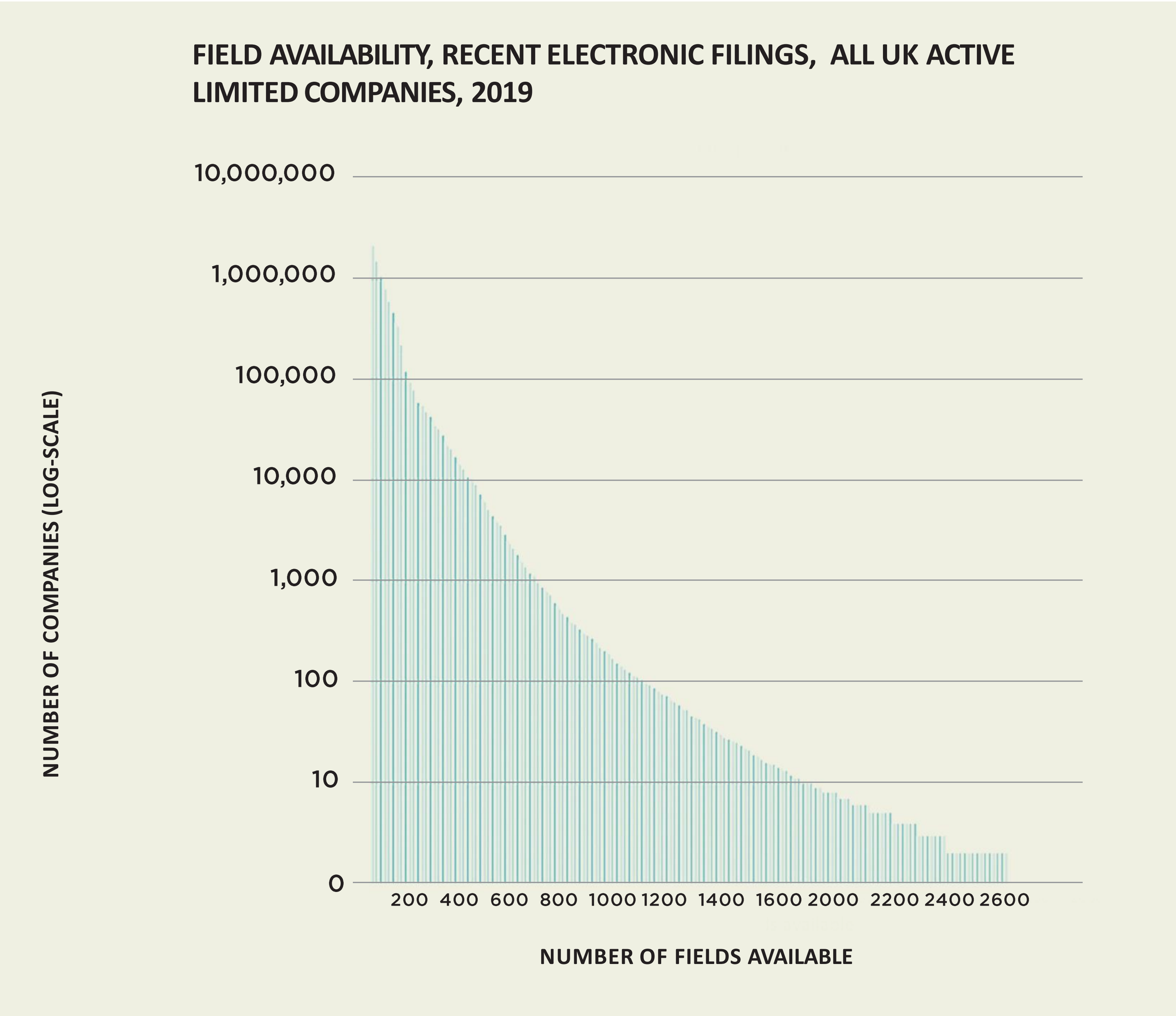
We enrich the standard company accounting data with registration and filing information and socio-economic geospatial data.

We then apply sophisticated modern machine-learning models to fully exploit our large structured datasets.

Our models are tolerant to large proportions of missing data and turn missing data patterns into powerful predictive features.



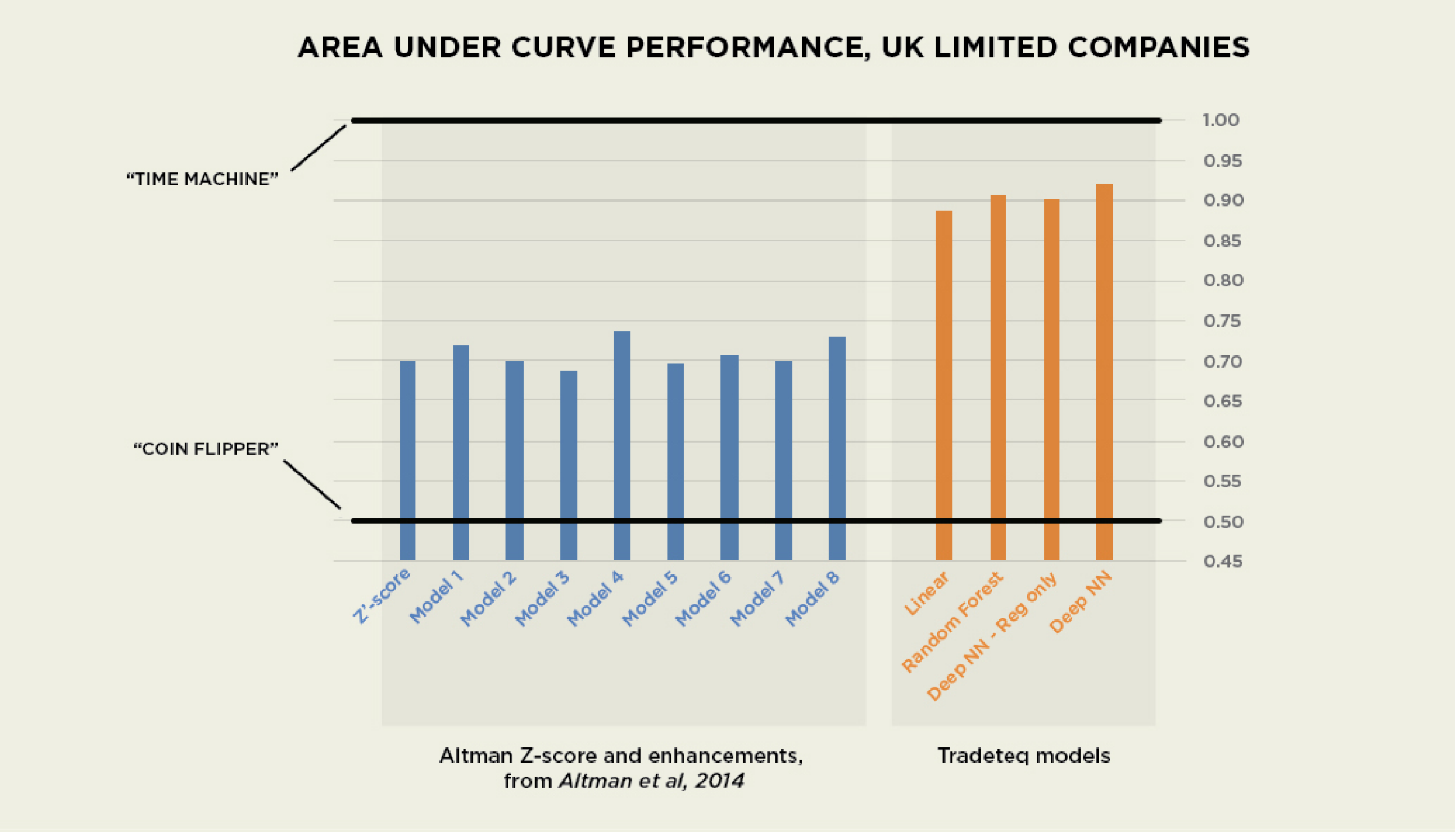
Left Source: Consumer Data Research Centre
Right Source: Tradeteq, Companies House



COMPARATIVE RESULTS

Tradeteq's models have much wider coverage than the Z-score model versions tested in [Altman et al, 2014] and never reject a company just because its assets are too low or because it has not reported a certain accounting indicator.

A combination of machine learning techniques with deep and broad data coverage allows the outperformance of traditional Z-score and similar models even on pure registration data, without using any accounting inputs.

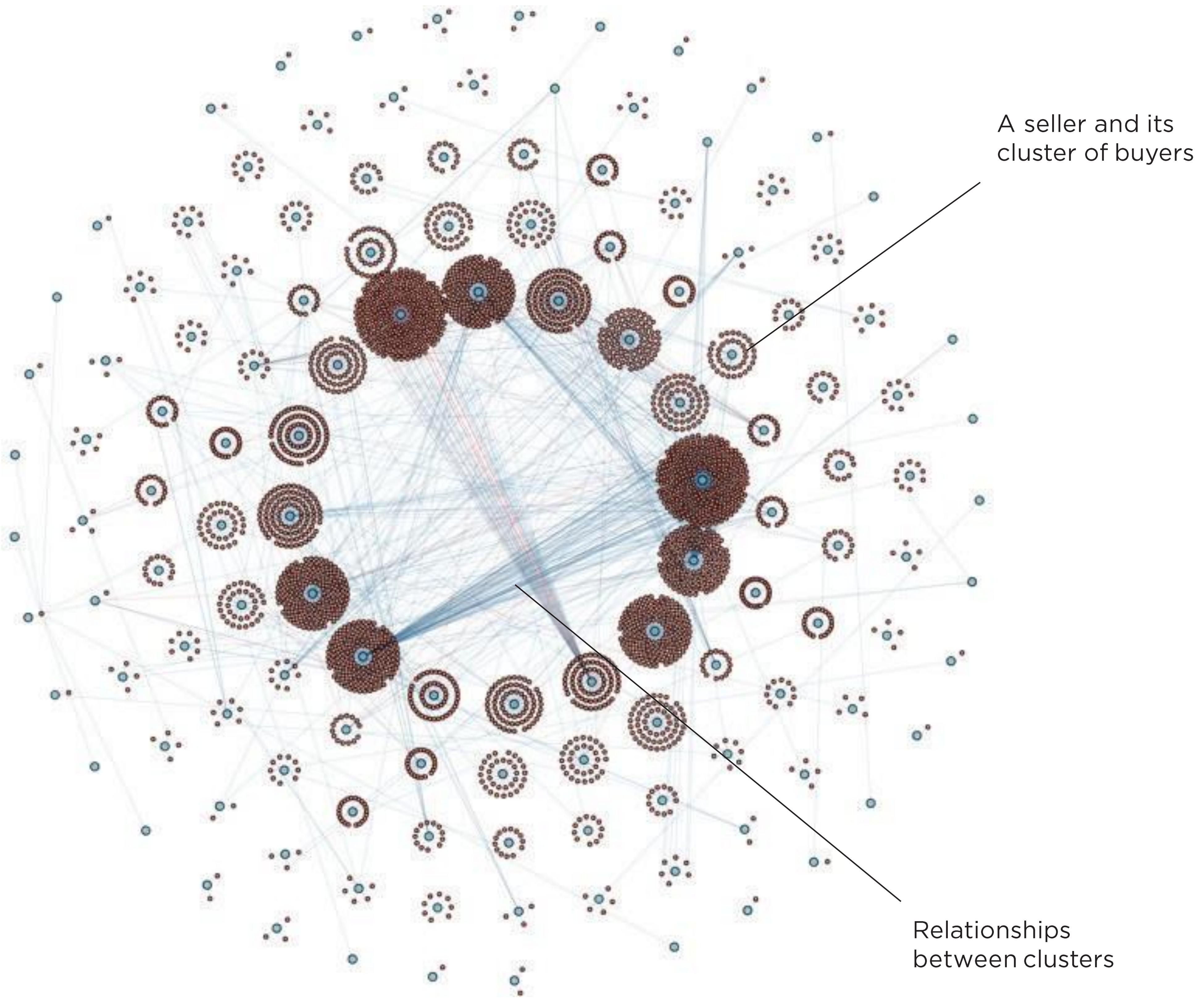


Source: Tradeteq
[Altman et al 2014] Altman, E.I., Iwanicz-Drozdowska, M., Laitinen, E.K. and Suvas, A., 2014. Distressed Firm and Bankruptcy Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-Score Model.

SUPPLY CHAIN GRAPH ANALYSIS

Company level information may be unavailable, unreliable and stale, especially in many emerging markets.

Supply chain graph analysis can allow much better credit predictions. These graphs contain a rich flow-type dataset associated with each graph edge.



Source: TradeTeq.
Anonymized transaction data for a sample portfolio

ADVERSARIAL LEARNING

As our credit models gain wider use, potential benefits of adversarial attacks increase. We are most concerned with *Offline Model Evasion* attacks (see https://github.com/mitre/advmlthreatmatrix/blob/master/pages/adversarial-ml-threat-matrix.md#adversarial-ml-threat-matrix)

Threat of Adversarial attacks limits model sharing and model transparency, so it is important for us to understand extent of the threat and possible defenses, for black box and white box attacks

A few links on Adversarial ML

A short tutorial https://www.toptal.com/machine-learning/adversarial-machine-learning-tutorial

A more formal and complete treatment https://www.sciencedirect.com/science/article/pii/S209580991930503X

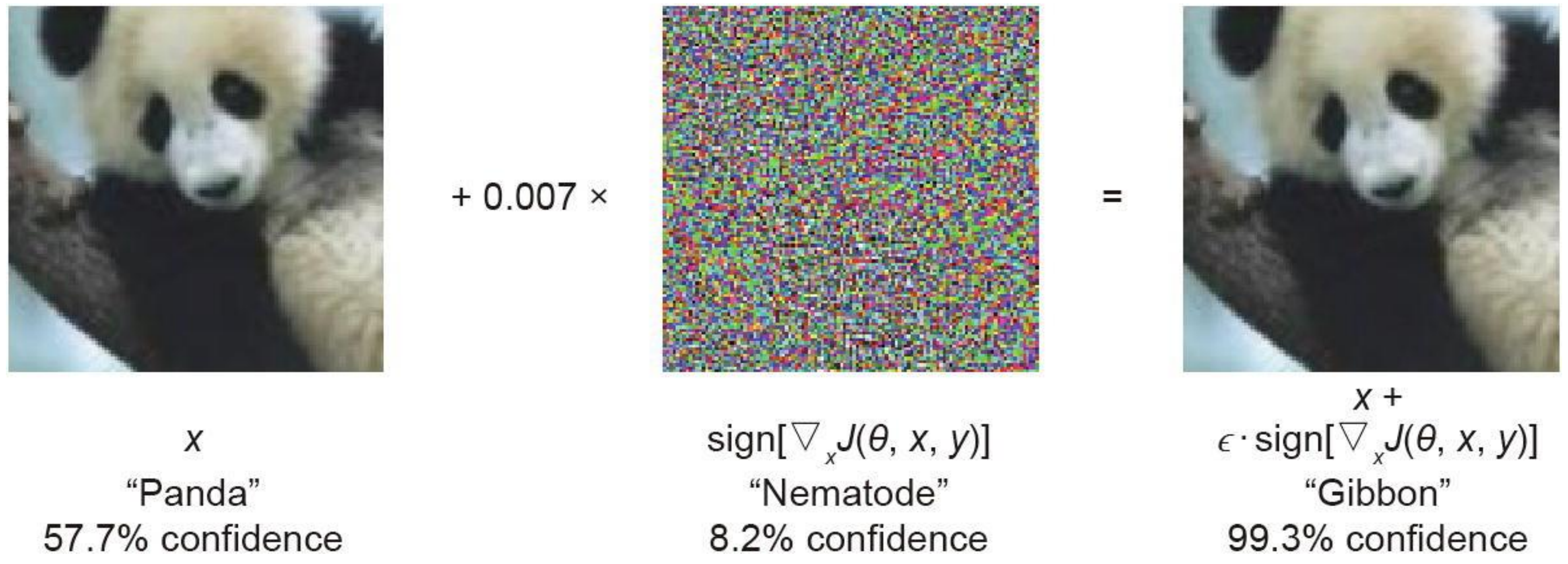


Image source: https://arxiv.org/abs/1412.6572 Ian J. Goodfellow, Jonathon Shlens, Christian Szegedy, "Explaining and Harnessing Adversarial Examples"

A ROUGH PLAN

1. Obtain company data → *I will share a link to a proprietary curated and pre-processed dataset*
2. Calibrate a credit prediction model for it → *a binary classification targeting is_failed status*
3. Establish which fields are most prone to manipulation
4. Design and perform adversarial model evasion attacks
5. *Design defenses against these attacks

DISCLAIMER

The material in this presentation has been prepared by Tradeteq Limited (Tradeteq) and is general background information about Tradeteq's activities current as at the date of this presentation. This information is given in summary form and does not purport to be complete. Information in this presentation, including forecast financial information, should not be considered as advice or a recommendation to Funders or potential Funders in relation to holding, purchasing or selling securities or other financial products or instruments and does not take into account your particular investment objectives, financial situation or needs. Before acting on any information you should consider the appropriateness of the information having regard to these matters, any relevant offer document and in particular, you should seek independent financial advice. All investments and securities, financial product, or instrument transactions involve risks, which include (among others) the risk of adverse or unanticipated market, financial developments.

This presentation includes forward looking statements including statements regarding our intent, belief or current expectations with respect to Tradeteq's businesses and operations, market conditions, results of operation and financial condition, capital adequacy, specific provisions and risk management practices. Readers are cautioned not to place undue reliance on these forward looking statements. Tradeteq does not undertake any obligation to publicly release the result of any revisions to these forward looking statements to reflect events or circumstances after the date hereof to reflect the occurrence of unanticipated events. While due care has been used in the preparation of forecast information, actual results may vary in a materially positive or negative manner. Forecasts, projections, and hypothetical examples are subject to uncertainty and contingencies outside Tradeteq's control. Past performance is not a reliable indication of future performance.