Systemic Risk Modelling and Early Warning Systems

Dr. Joel Janek Dabrowski
Dr. Conrad Beyers
Prof. Pieter de Villiers

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Overview

• Systemic risk research (Conrad)

• Modelling approach (Pieter)

• Early warning systems (Joel)
Systemic risk research
Complex dynamical systems
Layers of complexity

Fundamental interacting particles

Net 1

Net 2

Net 3

Context

Time evolution

Change

Damage
Emergent phenomena?

Conditional stability
Modelling financial systems
Layers of complexity

Interconnected financial entities

Macro-environment

Time evolution

Intervention

Legal

Shocks

Banks

Shadow sector

Insurers
Focus areas
Bank networks and shock propagation
Stress testing of banking systems

Input data
- UK public aggregate data
- USA granular customer level data

Top-down stress test model
- UK – RAMSI
- USA – FED model

Analysis
- Cross-check top-down & bottom up results
- Determine future scenarios

US & UK guidelines

Bank 1
- Bottom-up stress test submission

Bank 2
- Bottom-up stress test submission

Bank 3
- Bottom-up stress test submission

Bank 4
- Bottom-up stress test submission

...
Financial market macro-economic models

Macroeconomic Conditions (Underlying)

Central Bank + Regulator

Interbank market

Banks

Loan market

Households

Capital adequacy requirement
Penalties on default
Capital requirement infringement penalties

\[ Y \]

\[ \delta \]

\[ \tau \]

\[ \alpha \]

\[ \beta \]

\[ \theta \]

\[ \phi \]
Credit ratings

Greece

• Replicate ratings?
• How good are the ratings?
• Is US “risk-free”?
• Alternative ratings?

RSA
Financial regulation

Early warning systems

Finland, 1990–1995 and 2008 crises
Modelling approach
Data Science, Fusion and Machine Learning Research

Pieter de Villiers,
PhD (Cantab), M Eng (UP), B Eng (UP)

Department of Electrical, Electronic and Computer Engineering
Where we fit in:

- Department Electrical Electronic Computer Engineering
- Intelligent Systems Group
  - Robotics
  - Image processing
  - Machine Learning
  - Data fusion
- Data Fusion Group - Prof Pieter de Villiers
The Decision Loop

- **Hidden world state**
- **Model of an aspect of world of interest**
- **Senses and sensors**
- **Inference**
- **Decision**

Only projections of real world are observed.

Based on understanding/Previous observations.
Inference / Prediction

Determining the hidden/obscured

Parameters $\rightarrow$ Static Systems, Time invariant

States $\rightarrow$ Dynamic Systems, Time variant
Example: Fraud detection – true network
Example: Fraud detection - observed

Observed network
Systemic Banking Crisis
Early Warning Systems
Using Dynamic Bayesian Networks

Dr. Joel Janek Dabrowski
Dr. Conrad Beyers
Prof. Pieter de Villiers

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Maritime Piracy Project

(a) Initialize, (b) Pirate Drift, (c) Pirate Attack, (d) Pirate returned.
Systemic Banking Crises

Examples

• USA alone: 540 banks have failed since October 1, 2000\(^1\). 516 of which closed between 2007 and 2015.

• South Africa: **African Bank** collapse in 2014. Net loss R9.3bn in the fiscal year to September\(^2\).


Aim

Identify an imminent systemic banking crisis, according to banking and economic behaviour, before the crisis occurs.
Early Warning Systems

Surveyed Methods for early warning of banking crises\(^1,2\)

- ‘Signals’ Approach (Thresholding)
- Multivariable Logit Approach (Logistic regression)

Signals Approach

Approach:

• Variable values 24 months prior to a crisis are compared with the values during “tranquil” times.
• A variable signals a crisis if it crosses a particular threshold.

Drawbacks:

• Each variable is considered in isolation
• Information from each indicator is not aggregated
• Thresholding does not provide any indication of the severity of the crisis.
Logit Model Approach

Approach:

• The probability that a crisis occurs is assumed to be a function of a vector of explanatory variables.
• A logit model is fitted to the data for evaluating the probability of a crisis (logistic regression).

Drawbacks:

• Over-generalizes each class.
• Identifying a crisis is “too late”.
• Does not consider dynamics.
Our Approach

Use a dynamic Bayesian network (DBN) to model the temporal dynamics of variables and infer the probability of a crisis.

Pros:

Models temporal dynamics of the system.

Infers probability of a crisis which provides a “threat level” indication.

Cons:

Methods are more complex.
Model Evolution: *Linear Dynamic System*

\[
\begin{align*}
    h_{t-1} & \rightarrow h_t & \rightarrow h_{t+1} \\
    v_{t-1} & \rightarrow v_t & \rightarrow v_{t+1}
\end{align*}
\]

**Variables:**

- \( h_t \): State vector
- \( v_t \): Measurement vector
Linear Dynamic System (LDS)

\[ h_t = A_t h_{t-1} + \eta_t^h \]
\[ v_t = B_t h_t + \eta_t^v \]
\[ \eta_t^h \sim \mathcal{N}(\eta_t^h | \overline{h}_t, \Sigma_t^h) \]
\[ \eta_t^v \sim \mathcal{N}(\eta_t^v | \overline{v}_t, \Sigma_t^v) \]

transition model
emission model

\[ p(h_1) = \mathcal{N}(h_1 | \mu_{\pi}, \Sigma_{\pi}) \]

\[ p(h_t | h_{t-1}) = \mathcal{N}(h_t | A_t h_{t-1} + \overline{h}_t, \Sigma_t^h) \]
Model Evolution

Switching Linear Dynamic System

Variables:

- $h_t$: State vector
- $v_t$: Measurement vector
- $s_t$: Switching State vector
Proposed Model
Proposed Model at time $t$
Dataset

A dataset describing developed European economies with long time series is used\(^1\).

The variables, indicators or features include house prices, mortgages, mortgages to GDP, household loans, household loans to GDP, private loans, private loans to GDP, consumer price index, GDP, current account surplus to GDP, and loans to deposits.

A total of 19 systemic banking crises are included in the dataset.

Approach

• Given variables and crises periods.
• Define pre-crisis periods the 3 year period leading to the crisis.
• Given a set of models: Logit model, Signals Model, Hidden Markov Model, SLDS, and NB-SLDS.
• Leave-one-out cross validation:
  • For each model:
    • For each country:
      • Train the model on all other country data (leave referenced country out).
      • Try predict tranquil, pre-crisis, and crises periods for the referenced country.
      • Report the performance of the model.
  • Compare average performance of models
Desired Outcome

Pre-Crisis Period

Crisis Period

NB-SLDS Model Prediction

$p(\text{crisis})$

Performance Measures

- **Accuracy** describes the probability of correctly classifying a crisis.

- **Recall** is a *sensitivity* measure. It is a measure of the fraction crises detected.

- **Precision** is a *confidence* measure. It is a measure of the fraction of crisis detections that are actually crises.

- **F-score** is the harmonic mean between the precision and recall.
Performance Measures

\[
\text{Accuracy} = \frac{TP + TN}{N}, \quad \text{Recall} = \frac{TP}{TP + FN}, \quad \text{Precision} = \frac{TP}{TP + FP}
\]
Performance Measures

**Accuracy**

\[ \text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \]

**Recall**

\[ \text{Recall} = \frac{TP}{TP + FN} \]

**Precision**

\[ \text{Precision} = \frac{TP}{TP + FP} \]
Comparison Results:

Average regime detection results over all countries.

(Computed over the complete data sequence of the best performing features.)
Comparison Results:

Box-Whisker Plot for regime detection accuracy: The ideal method has ‘high values’ with ‘smaller’ boxes.
Lower Recall, Higher Precision

\[ \text{Accuracy} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)} + \text{False Negatives (FN)}}, \quad \text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Negatives (FN)}}, \quad \text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}} \]
Comparison Results:

Average crisis predictability results over all countries.

(Only evaluate pre-crisis period)
Comparison Results:

Box-Whisper Plot for **crisis predictability** accuracy: The ideal method has ‘high values’ with ‘smaller’ boxes.
Reference:

This presentation is based on the article:


(Top rated AI academic journal on Google Scholar)