RiskLab

CrisisModeler:
A Tool for Exploring Crisis Predictions

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Motivation

- An acute interest in new approaches to assess systemic risk
- Financial crises triggered by various shocks (unpredictable)...
- ...but widespread imbalances build-up ex ante (identifiable)
- Early-warning models to identify systemic risk at early stages

- How to...
  - ...compare model output and performance for methods?
  - ...assess impact of data/parameters on output/performance?

Early-warning indicators

- Text-book example of 2-class classification: crisis vs. tranquil
- To identify vulnerable states of an entity you need...
  - Dates of historical crisis occurrences
  - Indicators to identify sources of vulnerability
- Estimate probability of being in a vulnerable state (pre-crisis)
  - Signaling: Monitor univariate indicators
  - Non/linear approaches for combining indicators
- Set a threshold on the probability to optimize a loss function
  - Transforms probabilities into binary point forecasts (0/1)
  - Depends on preferences between type I/II errors

Previous literature

Literature

- Few objective comparisons of early-warning methods
- Bilateral tests (e.g. Peltonen, 2006; Marghescu et al., 2011)
- Builds upon the horse race in Holopainen & Sarlin (2015)

Key conclusions of the horse race

- Machine and ensemble learning approaches perform well
- Aggregation decreases variation in model performance

This paper

Contributions

- a generalized framework for modeling and evaluation
- a web-based general-purpose tool for modeling interaction
- case studies on European countries and banks

Objective

- Awareness project to improve transparency & comparability
- Plug in methods to study model output & performance, given
  - preference settings
  - evaluation exercises
  - metrics

Methods and exercises

- A horse race of multiple methods
  - Logit
  - KNN
  - Classification tree & Random forest
  - ANN
  - SVM
  - Ensembles (best of, voting, mean, weighted)
- Exercises
  - Resampled out-of-sample performance
  - Real-time recursive exercise
  - Full-sample (model description & current output)

Case study: European banks

- Data from Betz et al. (2013) & Lang et al. (2015)
  - Data for 500+ EU banks with $>$ EUR 1 bn in assets
  - Quarterly data spanning 2001Q1 - 2014Q1 (9776 complete observations with the chosen variables)
  - Events: Direct failures, state aid and mergers in distress
  - 292 distress observations (an event may span multiple quarters)
- Define pre-distress indicator as
  - 1-8 quarters prior to distress event
  - 1052 pre-distress observations

Variables

Class	Variable
Bank	Tangible capital to assets
Bank	Interest expenses to liabilities
Bank	Reserves to assets
Sector	Financial assets to GDP
Sector	Mortgages to loans, 1-year change
Sector	Securities to liabilities, 1-year change
Macro	Total credit to GDP
Macro	Total credit to GDP, 3-year change
Macro	House price deviation from trend
Macro	International investment position to GDP
Macro	Private sector debt to GDP
Macro	10-year bond yield, 1-year change

Recursive horse race

- Real-time recursive exercise
  - Test out-of-sample predictive performance (2007Q1–2013Q1)
  - Use only data available at each point in time (publication lags)
  - Remove distress period & 4 post-crisis quarters from data
  - For each quarter in recursion, remove 8 quarters from end of data (if no distress event present)

Results

Method	TN	TP	FN	FP	$U_r(\mu)$	AUC
k-NN	5167	473	85	1013	64.5%	0.89
Voting	5065	404	154	1115	50.2%	
Random forest	5424	356	202	765	48.7%	0.86
Best of	5424	356	202	756	48.7%	0.86
Weighted	5168	373	185	1012	46.7%	0.85
Mean	5106	358	200	1074	42.8%	0.84
SVM	4562	370	188	1618	34.1%	0.79
Logit	4496	355	203	1684	30.1%	0.78
Trees	5325	241	317	855	26.2%	0.59
Neural network	4891	280	278	1289	24.5%	0.74

Results with forecast horizon 12q

Method	TN	TP	FN	FP	$U_r(\mu)$	AUC
k-NN	4814	589	83	1252	66.9%	0.89
Random forest	5196	530	142	870	64.5%	0.88
Best of	5196	530	142	870	64.5%	0.88
Voting	4585	564	108	1481	59.4%	
Weighted	4608	549	123	1458	57.6%	0.87
Mean	4603	538	134	1463	55.9%	0.86
Neural network	4595	452	220	1471	42.9%	0.78
SVM	4180	483	189	1886	40.7%	0.79
Logit	4129	480	192	1937	39.4%	0.77
Trees	4591	417	255	1475	37.7%	0.69

Results with forecast horizon 4q

Method	TN	TP	FN	FP	$U_r(\mu)$	AUC
k-NN	5546	307	125	760	51.5%	0.83
Voting	5424	270	162	882	39.8%	
Random forest	5690	236	196	616	38.8%	0.79
Best of	5690	236	196	616	38.8%	0.79
Weighted	5574	213	219	732	30.5%	0.81
Mean	5547	195	237	759	26.5%	0.80
Neural network	5360	209	223	946	24.0%	0.74
Logit	4976	247	185	1330	22.9%	0.77
SVM	4920	219	213	1386	15.0%	0.71
Trees	4970	141	291	1336	-0.02%	0.61

CrisisModeler as a tool

- CrisisModeler provides...
  - access to a common general modeling framework
  - performance comparisons of any method
  - web-based interface for interaction with methods/parameters
  - browser/server-architecture - calculations performed on server in R, no installation required for end-user
- A preliminary demonstration version available on the web, with two default data sets

Thanks for your attention!