ML and Model Risk in Finance

Samuel N. Cohen

University of Oxford and Alan Turing Institute

with Christoph Reisinger and Victor Wang
and Łukasz Szpruch and Derek Snow

University of Oxford
Mathematical Institute

Oxford Mathematics

Mathematical Institute

Doesn't machine learning free us from needing models?

Modelling and machine learning

Mathematical Institute

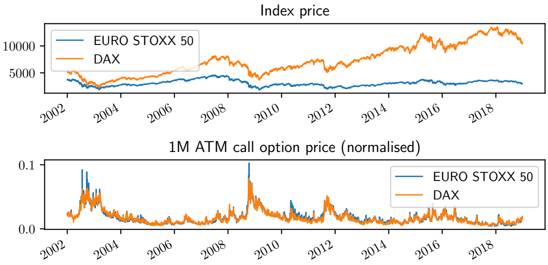
- Machine learning provides great modelling *flexibility*
- Neural networks / tree based models / Kernel methods all are tools for *expressivity* in approximating functions

- How we use these methods, and how we make them interact with data, is a modelling decision.
- The results of these methods have hidden assumptions.

An example application

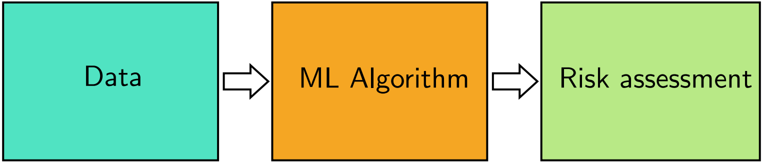
Mathematical Institute

- Risk calculation needs models (under real world probabilities) of risky outcomes.
- Options contain useful information, which may not be in basic prices.
- Estimating risks of option portfolios is useful.



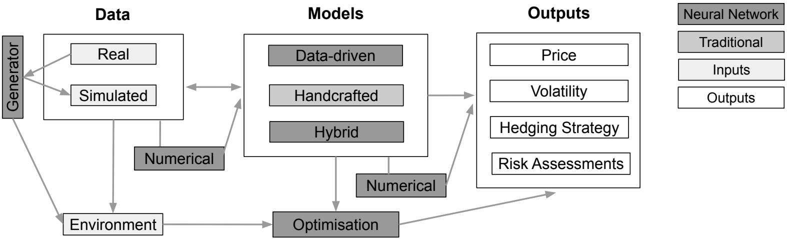
Let's build a model!

- We have a collection of inputs
  - Historical prices of the underlying index
  - Historical prices of vanilla options
- We have desired outputs
  - Price changes
  - Hedging strategies
  - Distributions of losses, value at risk



A more realistic pipeline

UNIVERSITY OF OXFORD
Mathematical Institute



We will discuss risks in each of these three columns.

Risks from data

Mathematical Institute

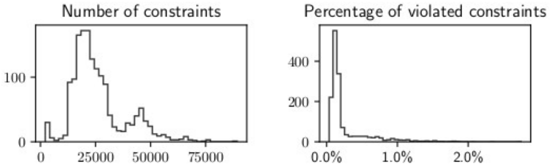
Biased Data

- Backward looking.
- Spurious Correlations.
- Sample disparity (e.g. geographic bias).
- Imbalanced and insufficient data.

Risks from data

Errors and preprocessing

- Recording errors.
- Timing errors.
- Inconsistent data
- Heavy tails



Static arbitrage violations for CME traded USDEUR option EOD prices 2008–2018

Potential Solutions

UNIVERSITY OF
OXFORD
Mathematical
Institute

- Domain knowledge – finance is not image processing!
- Common methodology and standardized test cases

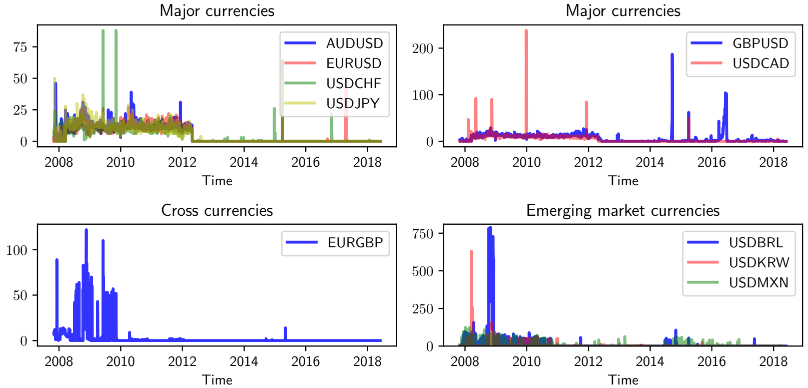
- Synthetic data for quantity and bias correction
- Market simulation

- 80% of a data scientist's time is spent on data preparation.

Example solutions

Mathematical Institute

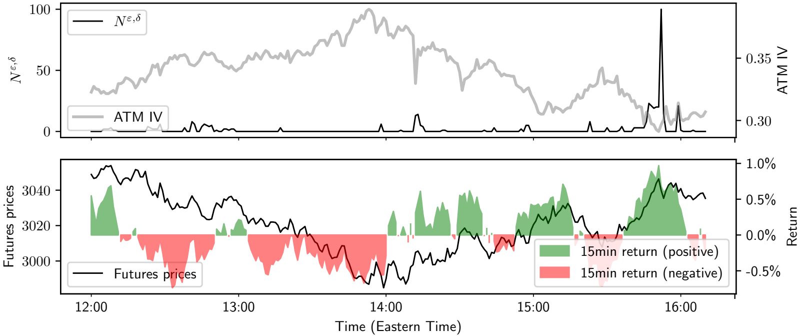
We have a toolbox to identify and remove arbitrage from historic data (github.com/vicaws/arbitragerepair)



OTC Forex options on Bloomberg

Example solutions

If considering intraday data, the problem is even worse.



12 June 2020, Emini S&P500 monthly European call options, 1 min resolution.
$N^{\epsilon,\delta}$=#perturbations outside bid–ask spread needed to eliminate arbitrage.

Synthetic data

- Classical models have well understood performance.
- They allow us to use our experience in building models.
- We can also consider counterfactuals.
- Testing models on synthetic data is critical.

Risks from models and methods

Four typical sources of model risk:

- Structural risk
- Adversarial attack
- Sensitivity
- Model drift

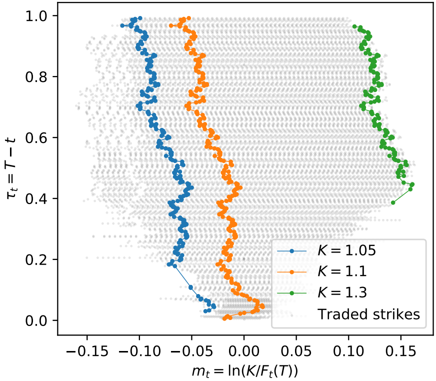
Model risk – Structural

Mathematical Institute

- ML can be misleading in surprising ways
- Model richness is constrained by numerical methods, rather than explicit modelling choices
- The questions we ask often hide modelling assumptions
  - Prediction set – Markov assumption
  - Summed quadratic loss – no-correlation assumption
  - Data driven using historical data – no market impact

Model risk – Structural

How we parameterize our models can be suprisingly important

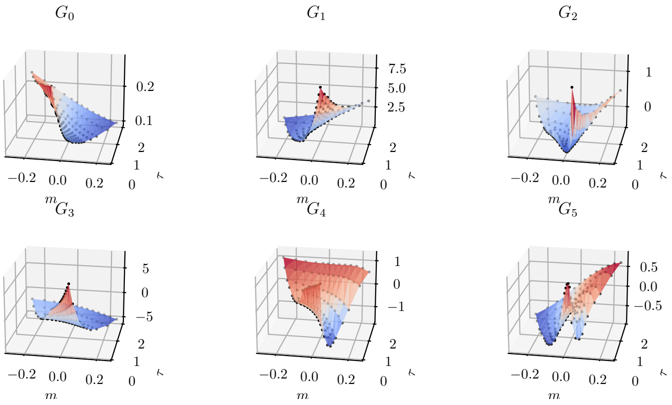


CME EURUSD options with expiry 6 March 2020 from first listing

Model risk – Structural

UNIVERSITY OF OXFORD
Mathematical Institute

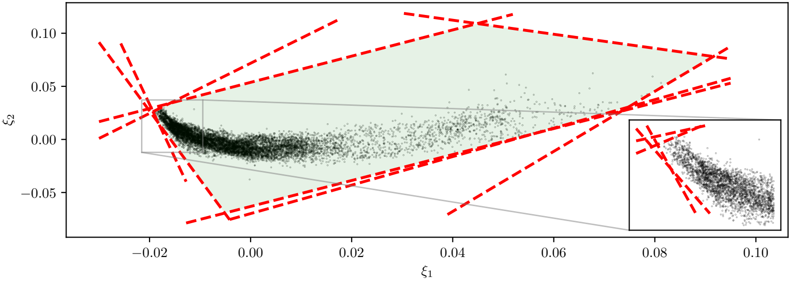
For our EuroSTOXX50 options model



Model risk – Adversarial

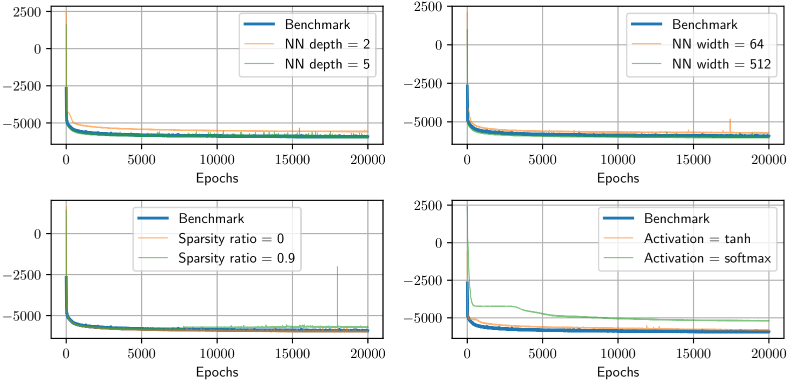
UNIVERSITY OF OXFORD
Mathematical Institute

- Arbitrage is a classic adversarial attack
- Dynamic and static arbitrage are different



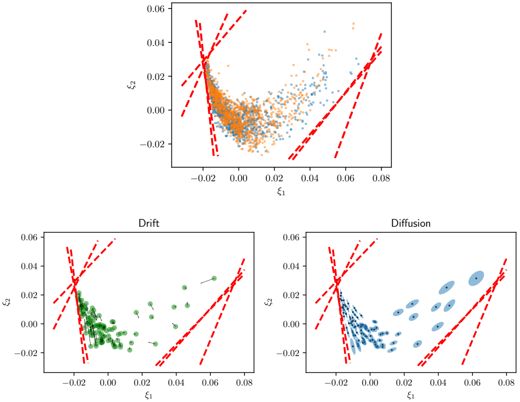
Model risk – Sensitivity

- Performance depends on a wide range of inputs
- These are an opaque form of model selection



Risk in outputs

- We learn a model for the drift and diffusion of the first two factors, ensuring no static arbitrage
- Remaining factors are fitted as independent OU processes



Risk in outputs

UNIVERSITY OF OXFORD
Mathematical Institute

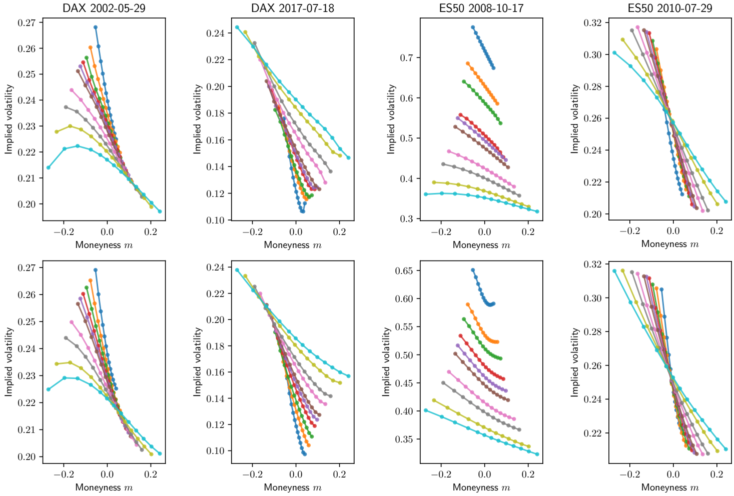
- The most fundamental risk is that a model will not calibrate correctly, so ensuring output appears plausible is of first importance.
- A good model should replicate the full range of observed data, particularly when observed from directions which were not used in training.

Risk in outputs – Plausible outputs

Implied Volatility surfaces

Real data

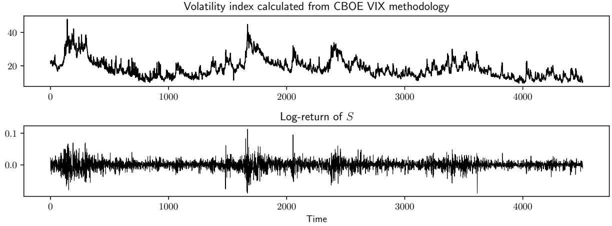
Simulation



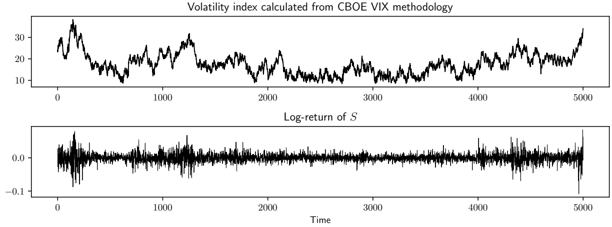
Risk in outputs – VIX

Mathematical Institute

Real data



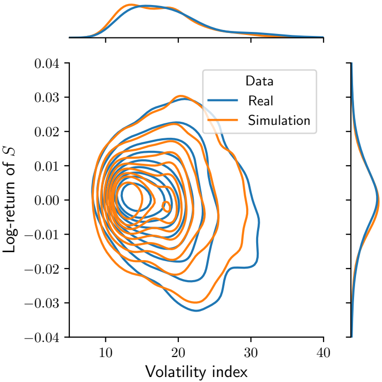
Simulation



Risk in outputs – VIX

EURO STOXX 50 index options

UNIVERSITY OF OXFORD
Mathematical Institute



Performance and Risk

- Given ML models are less explainable than traditional approaches, they are only worthwhile if they result in a performance gain.
- Performance can be measured both in terms of statistical fit and predictive power, and in terms of reducing computational cost
- Generally, ML methods will be much more expensive to train, but may be cheaper to run.

Value at Risk

- We can use our model to compute risk profiles for various options portfolios.
  - Outright calls and Delta-hedged calls
  - Delta spreads, Delta butterflies, Delta-neutral strangles
  - Risk reversal, Calendar spreads, VIX
- We use the historical innovations (to allow for unmodelled and higher-order correlation effects) from our training data
- For comparison, we also use a Filtered Historical Simulation approach, from a time-series model on the Heston parameters.
- Given the neural-SDE approach does not involve additional option pricing, it is much more computationally efficient.

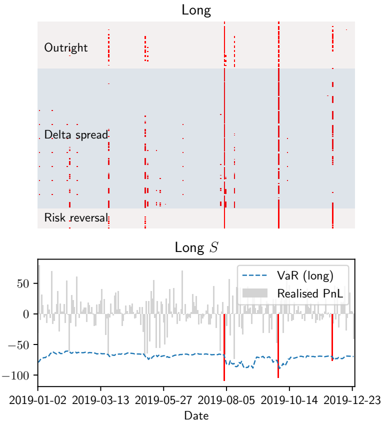
1-day 0.99-Value at Risk

University of Oxford
Mathematical Institute

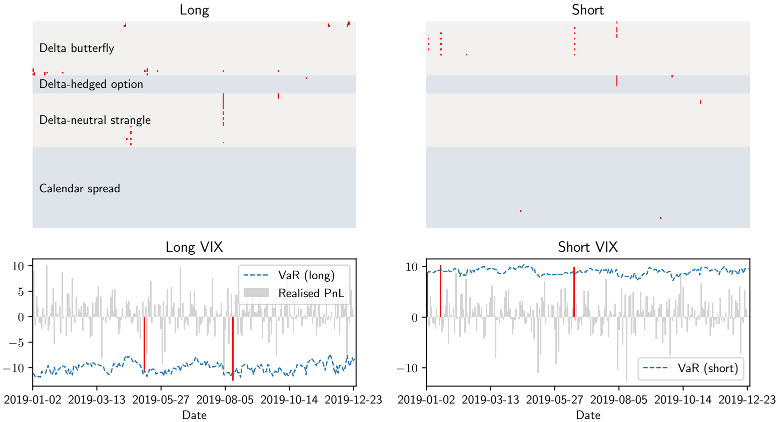
	Neural-SDE			Heston-EWMA FHS		
Coverage ratio median	0.9921			0.9881		
Coverage ratio mean	0.9887			0.9742		
Kupiec PF (two-sided)	6.92%			25.23%		
Kupiec PF (one-sided)	6.92%			25.23%		
Christoffersen independence	0.70%			11.03%		
Conditional coverage	3.53%			24.88%		
Basel committee traffic light	69.1%	29.7%	0.5%	62.4%	25.9%	10.8%

1-day 0.99-Value at Risk

UNIVERSITY OF OXFORD
Mathematical Institute

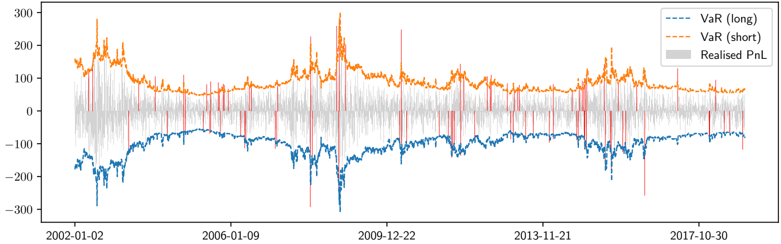


1-day 0.99-Value at Risk



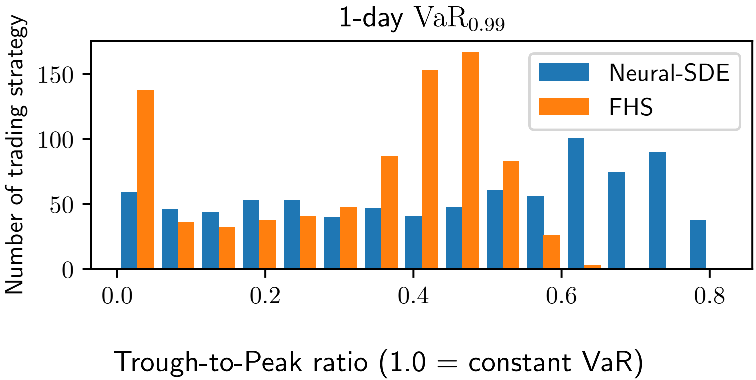
1-day 0.99-Value at Risk (training sample)

UNIVERSITY OF OXFORD
Mathematical Institute



1-day 0.99-Value at Risk – procyclicality

Mathematical Institute



1-day 0.99-Value at Risk – computational time

UNIVERSITY OF OXFORD
Mathematical Institute

	Simulate & revaluation		Repair arbitrage	
	nSDE	FHS (Heston)	nSDE	FHS (Heston)
Expected time (ms)	5.0	147.3	14.3	N.A.
Std. time (ms)	0.3	58.7	7.1	N.A.

Table: Average and standard deviation of the elapsed time for simulation one risk scenario.

Conclusions

Mathematical Institute

- ML is a powerful numerical tool, and gives flexible modelling
- Risk management still requires expert knowledge
- Benchmarking and testing critical
- Explainability and monitoring remains a challenge
- Potential benefits mean it's certainly worth pursuing!

References

- SNC, C Reisinger, S Wang, *Detecting and repairing arbitrage in traded option prices*, App Math Fin, 2021 (arXiv:2008.09454)
- SNC, C Reisinger, S Wang, *Arbitrage-free neural-SDE market models*, 2021 (arXiv:2105.11053)
- SNC, C Reisinger, S Wang, *Estimating risks of option books using neural-SDE market models*, 2022 (arXiv:2202.07148)
- SNC, D Snow, Ł Szpruch, *Black-box model risk in finance*, 2021, in *Machine Learning and Data Science in Financial Markets* (to appear) (arXiv:2102.04757)