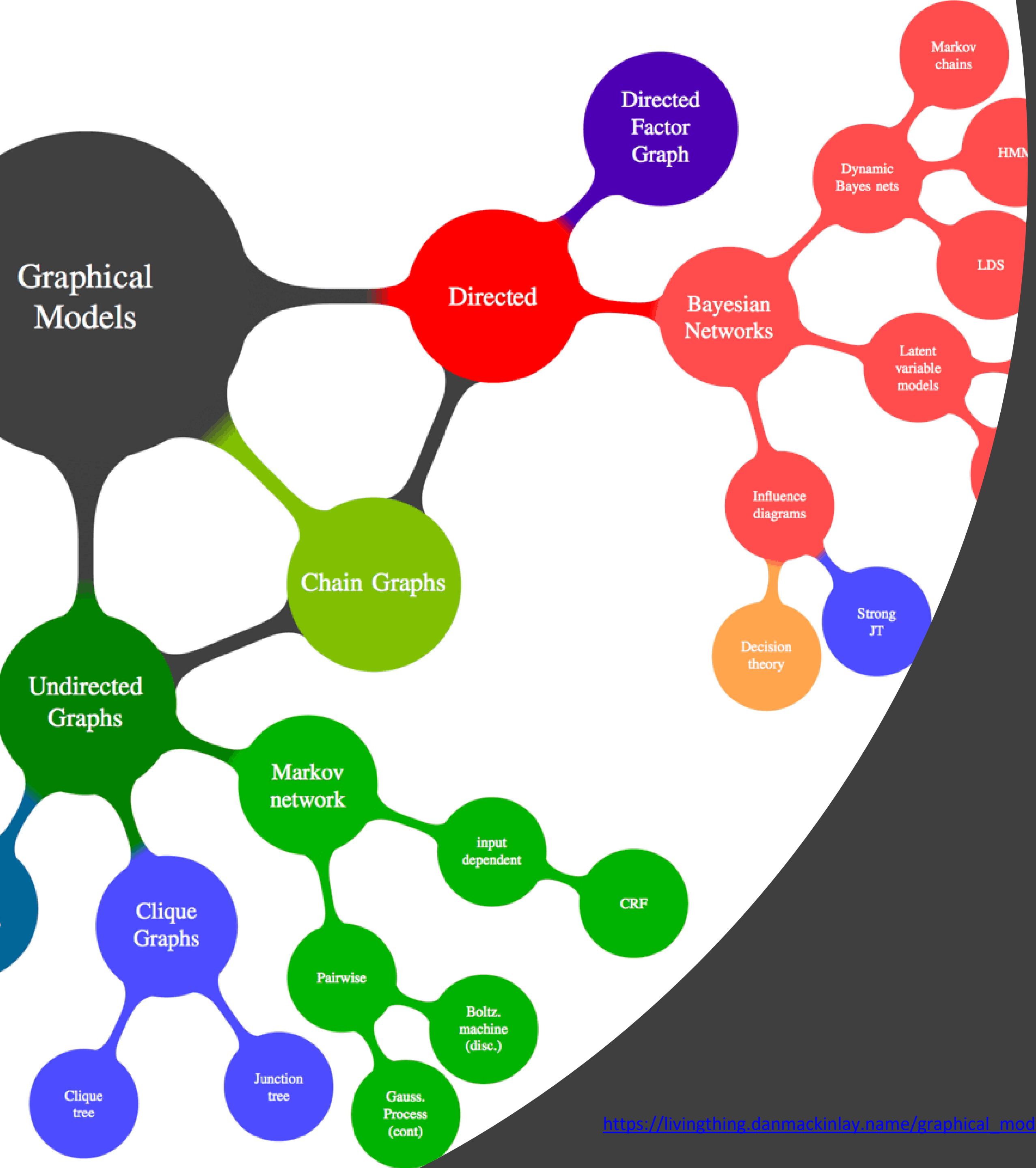


https://livingthing.danmackinlay.name/graphical_models.html

Connections, correlations, causality & coherence

Probabilistic graphical models – a framework for sparse prediction and coherent stress testing, in Canadian capital markets

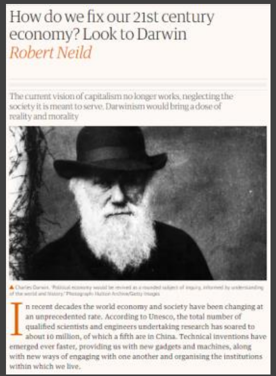
How I stopped worrying & learned to love uncertainty.

In memory

Robert Neild – 1924-2018

- British Keynesian economist who influenced Labour policy and whose other fields of interest included oysters and their aphrodisiac powers
- *I remember a damascene moment when, in early 1974 (after playing round with concepts devised in conversation with Nicky Kaldor and Robert Neild), I first apprehended the strategic importance of the accounting identity*

– Wynne Godley.



How do we fix our 21st century economy? Look to Darwin

Robert Neild

The current vision of capitalism no longer works, neglecting the society it is meant to serve. Darwinism would bring a dose of reality and morality

In recent decades the world economy and society have been changing at an unprecedented rate. According to Unesco, the total number of qualified scientists and engineers undertaking research has soared to about 10 million, of which a fifth are in China. Technical inventions have emerged ever faster, providing us with new gadgets and machines, along with new ways of engaging with one another and organising the institutions within which we live.

> “We need to put aside the long-established Newtonian vision of a harmonious economy with negligible innovations

Abstract

Two key objectives of macroprudential modelling are to measure

interconnectedness between financial **products**, **benchmarks** & institutions, from **public data**, and

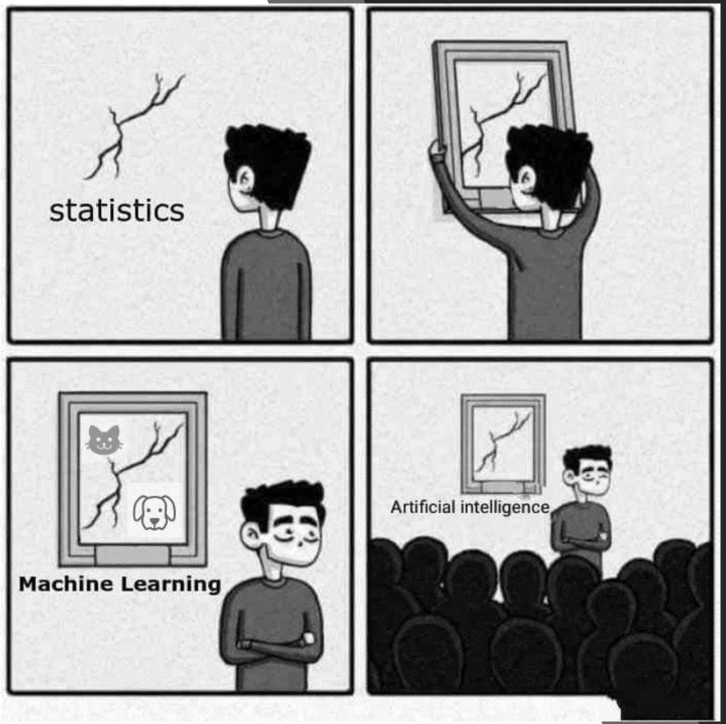
resilience of the system by conducting **coherent stress tests**.

A tool that has emerged from the machine learning community is (Bayesian) **probabilistic graphical models** which offer algorithms:

Information filtering networks - parsimonious, performant

Consistent treatment of probabilities (frequentist vs. subjective) & expert domain knowledge, intuitive

ML for economics



- ***Bayesian networks** are to probability calculus what spreadsheets are for arithmetic.*

  -- Conrady and Jouffe, 2015

- *Currently, **Bayesian Networks** have become one of the most complete, self-sustained and coherent formalisms used for knowledge acquisition, representation and application through computer systems.*

  -- Bouhamed, 2015

- *The core idea at the heart of **model-based machine learning** is that all the assumptions about the problem domain are made explicit in the form of a model. In fact, a model is just made up of this set of assumptions, expressed in a precise mathematical form. These assumptions include the number and types of variables in the problem domain, which variables affect each other, and what the effect of changing one variable is on another variable.*

  - Winn and Bishop 2018

A good player goes where the puck is. A great player goes where the puck is going to be. - Wayne Gretzky

Bayesian graphical models

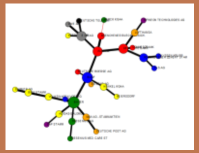
♦parsimonious interconnectedness ♦ coherent stress testing

Connections

- Amplification transmission
- E.g. for products
- Filter strong from spurious – **Information filtering networks** – cf GLASSO
- Clustering

Correlation

- Given **historical data**, standard measure of interconnectedness
- Graphical **visualization** e.g. MST → **insight**
- **Association**



Conditional

- **Conditional probabilities** on graph define ML model
- Conditional expectations – regression, prediction ("supervised learning")

Coherence

- Coherent stress tests
- Combine frequentist & subjective probs
- And expert knowledge – esp. cause & effect

Causality

- Correlation does not imply…
- See. Do. Imagine.
- Cognitive
- Why?

Systemic risk & models

Definition of systemic risk

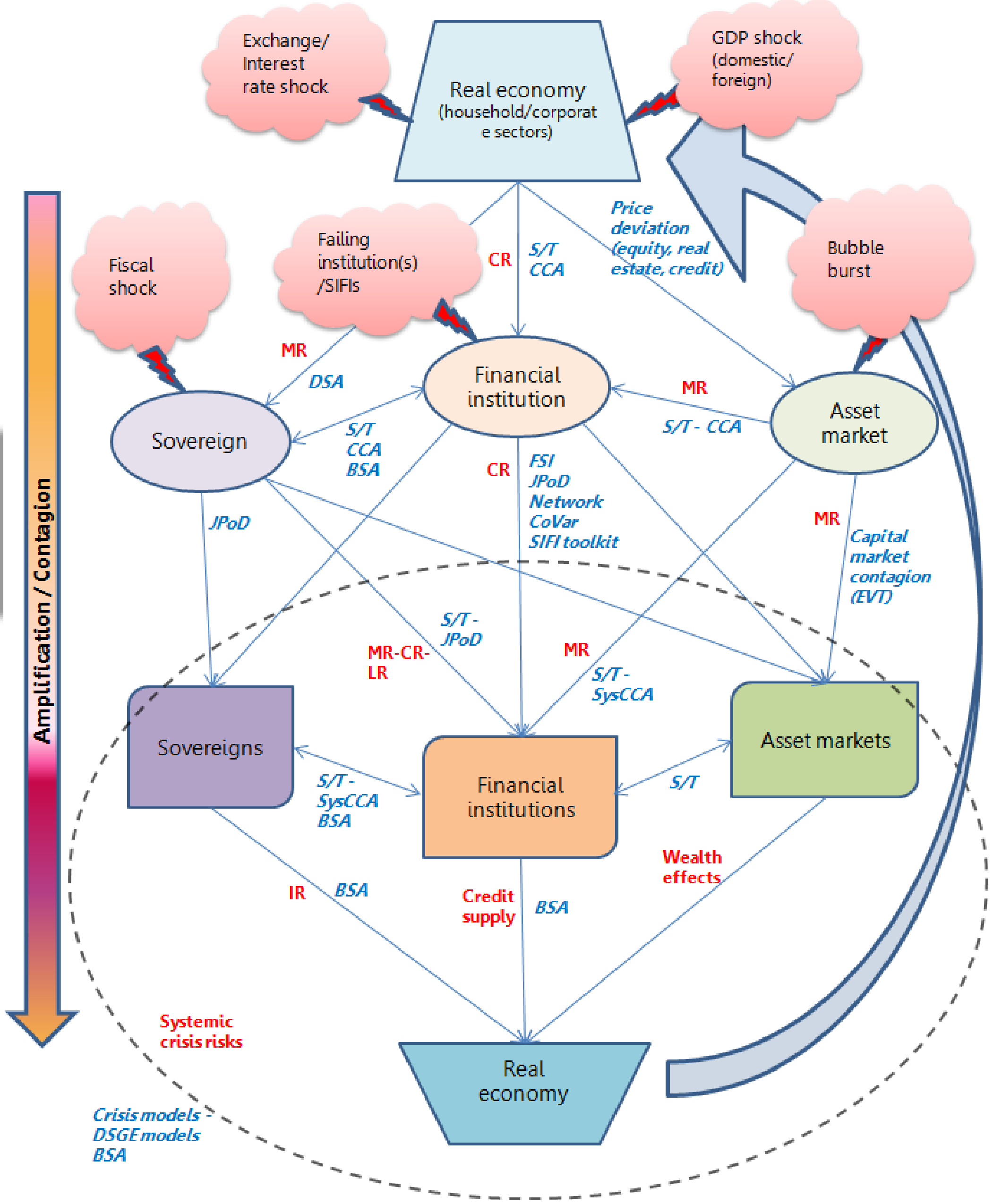
Phases of a crisis

Systemic Risk

Systemic risk related to capital markets

3. In this Act, systemic risk related to capital markets means a threat to the stability of Canada's financial system that originates in, is transmitted through or impairs capital markets and that has the potential to have a material adverse effect on the Canadian economy.

- MR: Market risk
- CR: Credit risk
- FSI: Financial Soundness Indicators
- T-model: Threshold Model
- DSA: Debt Sustainability Analysis
- CCA: Contingent Claims Analysis
- BSA: Balance Sheet Approach
- JPoD: Joint probability of default
- S/T: Stress testing
- EVT: Extreme value theory



Legend: MR: market risk; IR: Interest rate risk; CR: credit risk; DSA: debt sustainability analysis; S/T: stress testing; CCA: Contingent Claims Analysis; SysCCA: Systemic CCA; FSI: Financial Soundnes indicators; JPoD: Joint probability of Default; EVT: Extreme Value Theory

http://ccmr-ocrmc.ca/wp-content/uploads/cmsa-consultation-draft-revised-en.pdf

Source: SysMo toolkit (IMF)

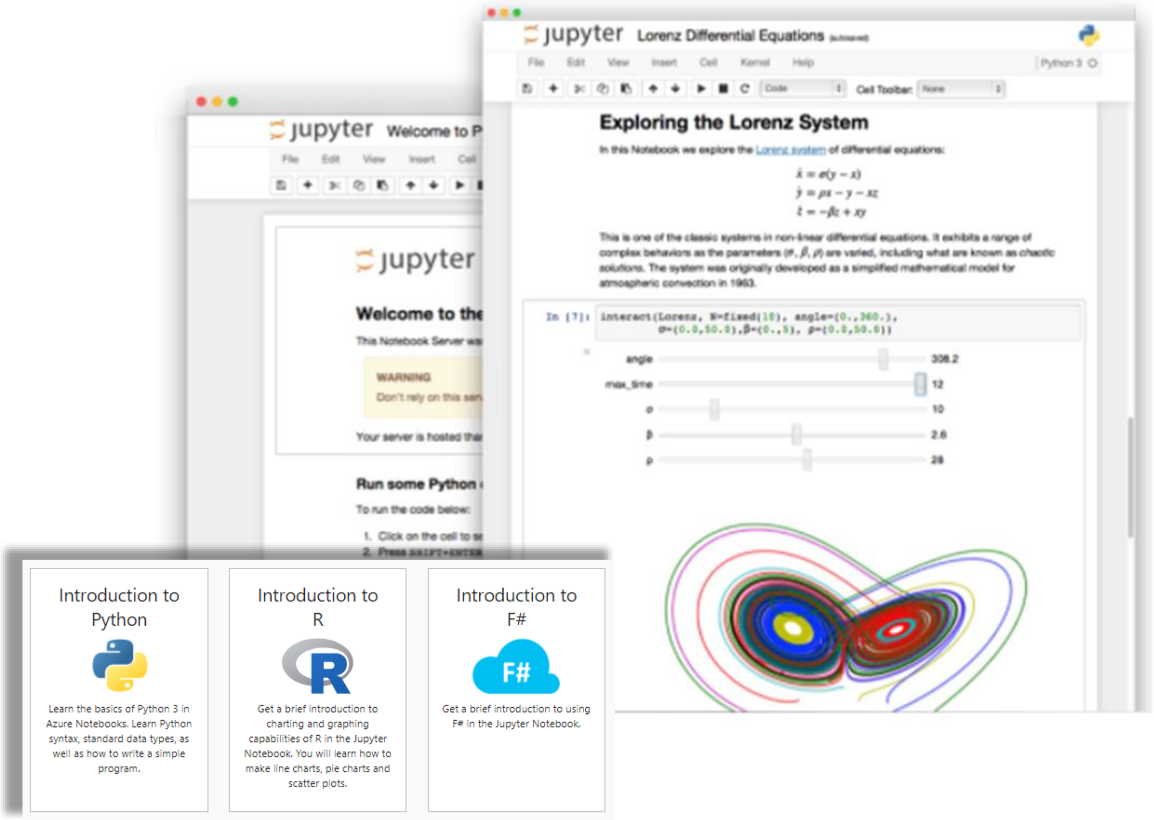
Macropru oversight through a crisis

Macroprudential oversight	Phases of crisis	Model / Indicators	Examples
Risk identification • Vulnerabilities • Triggers	I. Build-up of vulnerabilities & imbalances	• Early-warning (EWI) • Financial soundness (FSI) • Market intelligence • Backtesting	• Indebtedness of governments, sectors, institutions, households
Risk assessment • Transmission channels • Severity of losses \$ • Resilience • Likelihood $\mathbb{P}$	II. Exogenous aggregate shocks	• Macro stress-test (ST) on resilience of financial system • Risks: market, credit, liquidity	• MFRAF ST
	III. Amplification and propagation	• Contagion & spillover (FIs, sectors, countries) • Impact to real economy	• Battiston et al: DebtRank • Duarte & Eisenbach: Aggregate Vulnerability fire-sale spillover • Cont
Risk mitigation	Address any or all of the 3 phases	• Impact assessment of proposed measures	• See above

Source: Sarlin 2014

Jupyter notebooks

> *Let us change our traditional attitude to the construction of programs: Instead of imagining that our main task is to instruct a computer what to do, let us concentrate rather on explaining to human beings what we want a computer to do.*
>
> – Donald Knuth



- ❑ The Jupyter Notebook is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations and narrative text.
- ❑ Render
  - ❑ Github
  - ❑ Nbviewer - https://nbviewer.jupyter.org
- ❑ Host
  - ❑ Binder
  - ❑ Anaconda
  - ❑ Azure Notebooks
    - ❑ https://notebooks.azure.com/
- ❑ Also: JupypterLab

jupyter

Model demos

Azure Notebooks

julia

https://notebooks.azure.com/ian-buckley/projects/systemic-risk

FSI
- Filtering R

EWI
- CrisisMetrics*
- Azure ML Studio*

Resiliency
- CoVaR
- SRISK R Py

Network construction
- Entropy NRM R
- Bayesian R
- CIMDO Py
- Corr MST FNA*

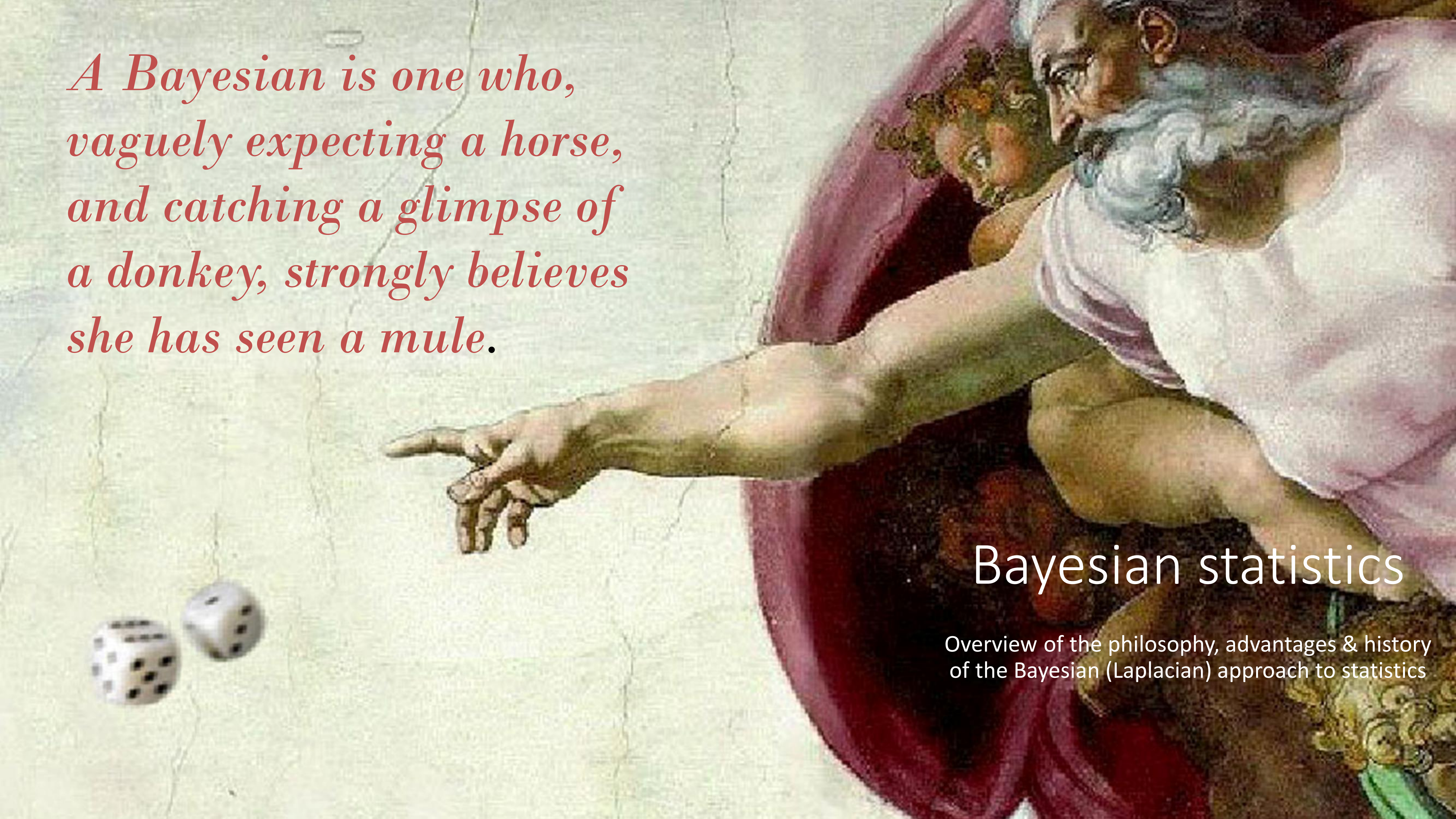
Network analytics
- DebtRank NRM R
- NEVA Py
- igraph

Economic
- ABM-OFR NetLogo
- ABM-ABCE Py
- SFC Py
- Keen Minsky Py

AI/ML
- PGMs & PP
  - PyMC3
  - Infer.NET
  - DoWhy

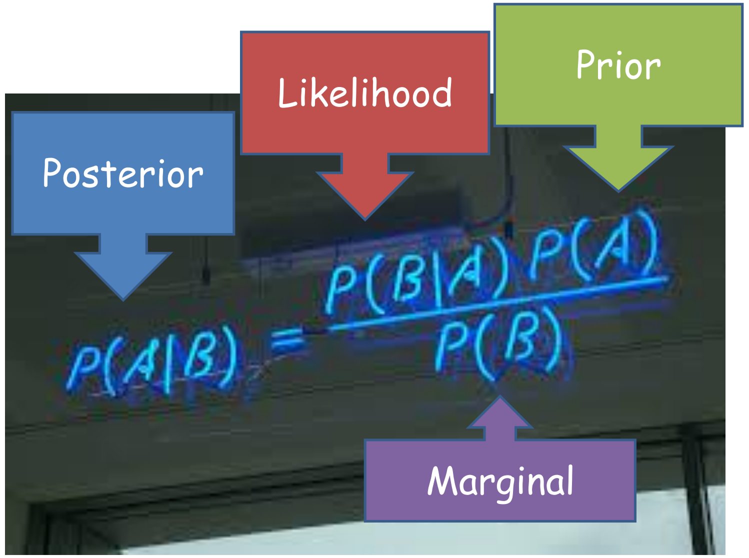
Visualization
- Corr MST FNA*
- KeyLines*
- Ndtv R

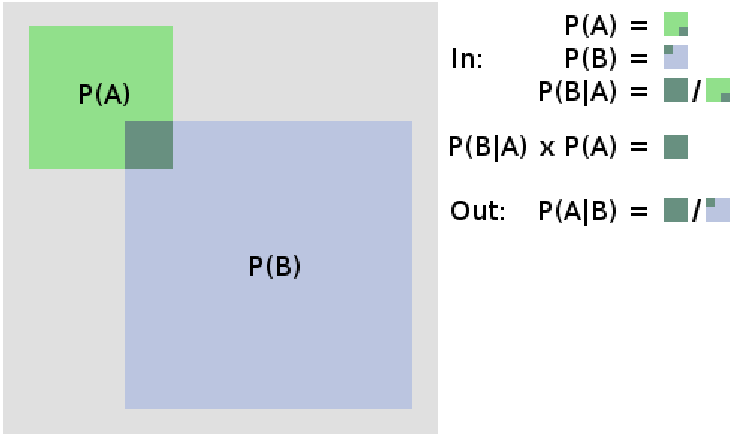
* Commercial


A Bayesian is one who, vaguely expecting a horse, and catching a glimpse of a donkey, strongly believes she has seen a mule.
Bayesian statistics
Overview of the philosophy, advantages & history of the Bayesian (Laplacian) approach to statistics

Bayesian vs Frequentist

	Frequentist	Bayesian
Inputs	Data	Data **+ prior**
Uncertainty measurement	Confidence interval	Credible interval
Assess significance	Null hypothesis tests $p(y\|H_0)$	Direct interpretation of the **posterior** $p(\theta\|y)$
Basic concept	Relative freq of an event	Bayes theorem
Probabilities	**Inherent property** of random phenomena in long run	**Plausible knowledge**
Parameter estimate	Point	Distribution / sample



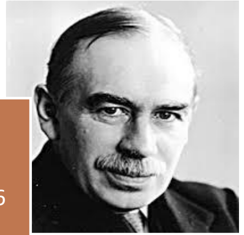


Innovators

Bayesians

Bayes
- 1702–1761

Laplace
- 1749–1827



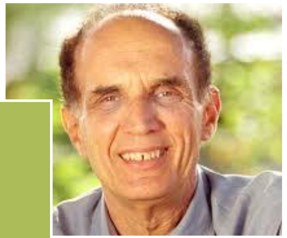
Keynes
- 1883-1946

Cox
- 1898-1991

Ramsey
- 1903-1930

De Finetti
- 1906–1985

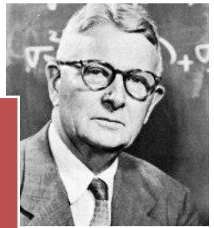
Jaynes
- 1922–1998



Efron
- 1938-

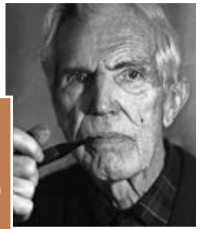
Bayarri
- 1956-2014

Causality

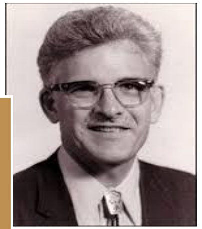


Wright
- 1889-1988

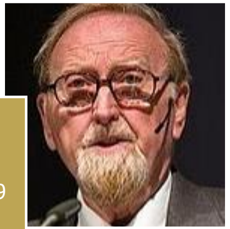
Burks
- 1902-1943



Haavelmo
- 1911 –1999



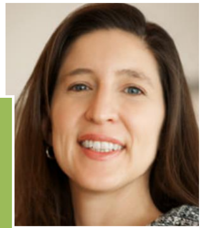
Duncan
- 1921-2004



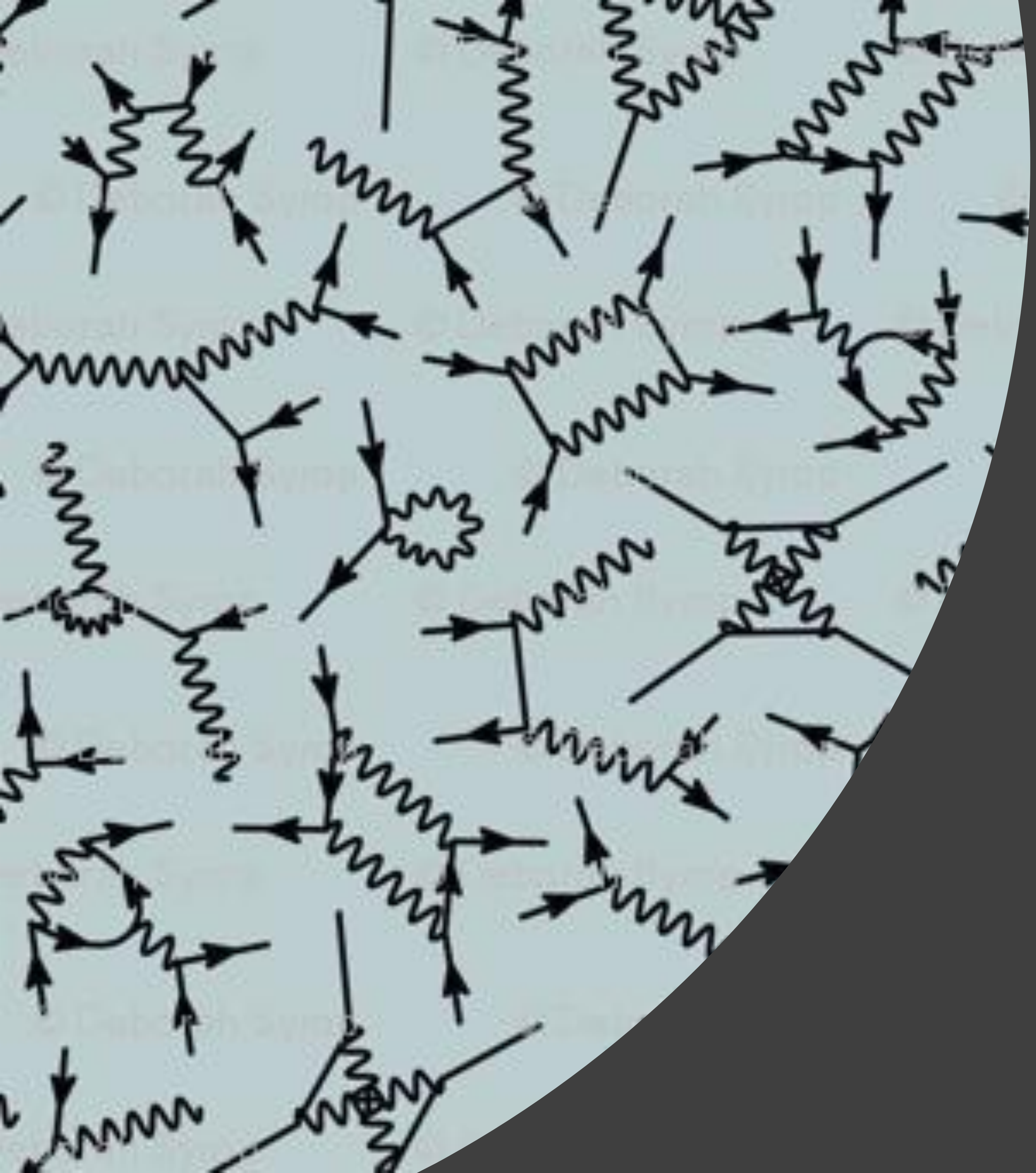
Granger
- 1934-2009

Pearl
- 1936-

Heckman
- 1944-



Athey
- 1970-



Probabilistic graphical models

Diagrammatic representations of probability distributions

People – Bayesian graphical models

BG-VAR

Ahelegbey

Billio

Information filtering networks

Aste

Di Matteo

Coherent stress testing

Rebonato

Denev

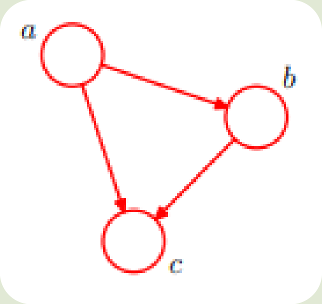
Model-based machine learning

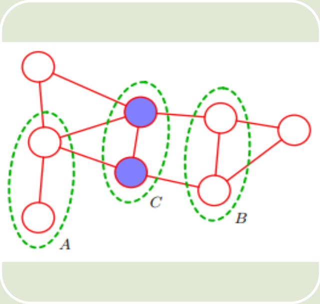
Bishop

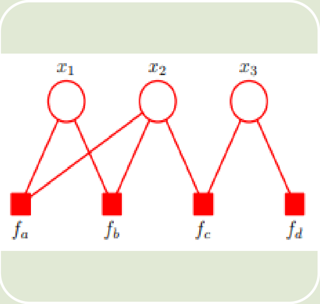
Winn

Graphical models

- A graph comprises
  - **nodes** (*vertices*) connected by
  - **links** (*edges* or *arcs*).
- In a probabilistic GM, each
  - node represents a *random variable*
  - links express *probabilistic relationships* between them







Bayesian networks
- Directed DAG
- causal

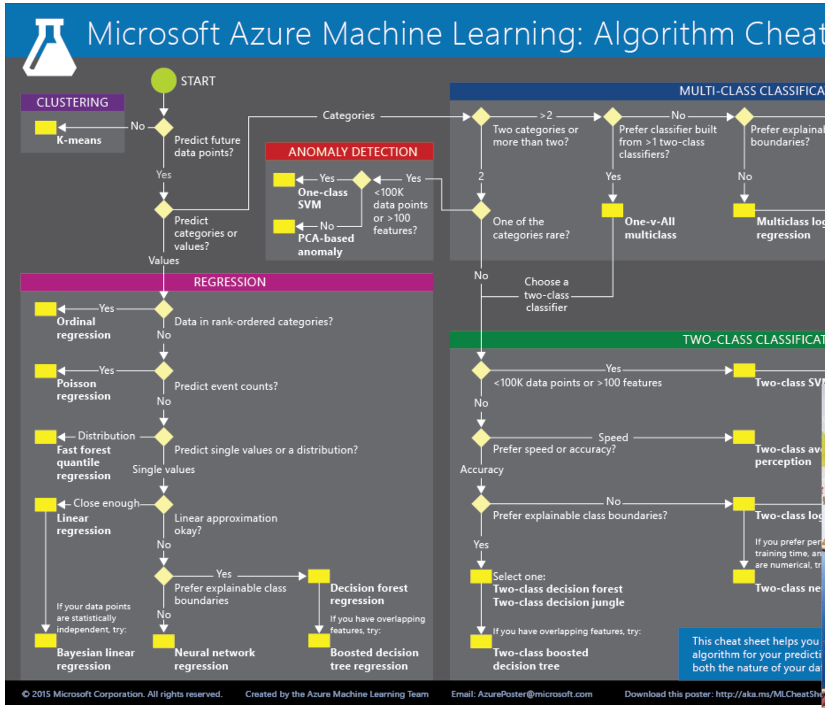
Markov random fields
- undirected

Factor graphs
- factorize PDF
- message passing algorithms

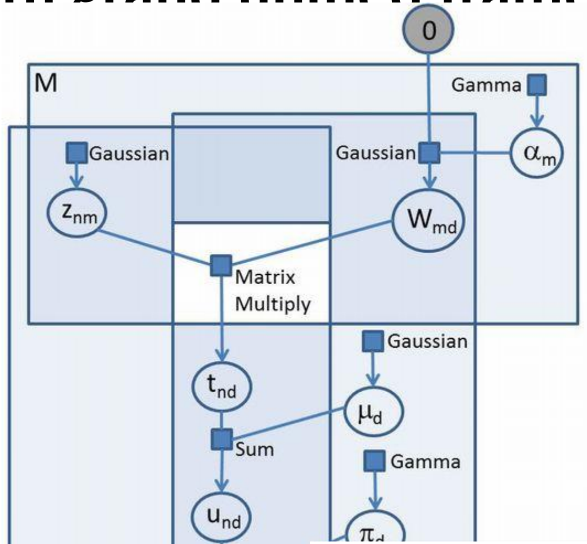
https://www.microsoft.com/en-us/research/uploads/prod/2006/01/Bishop-Pattern-Recognition-and-Machine-Learning-2006.pdf

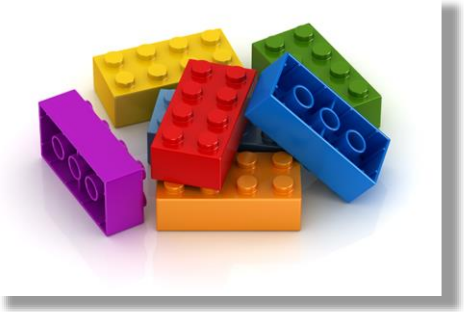
Model-based machine learning

Choose a method



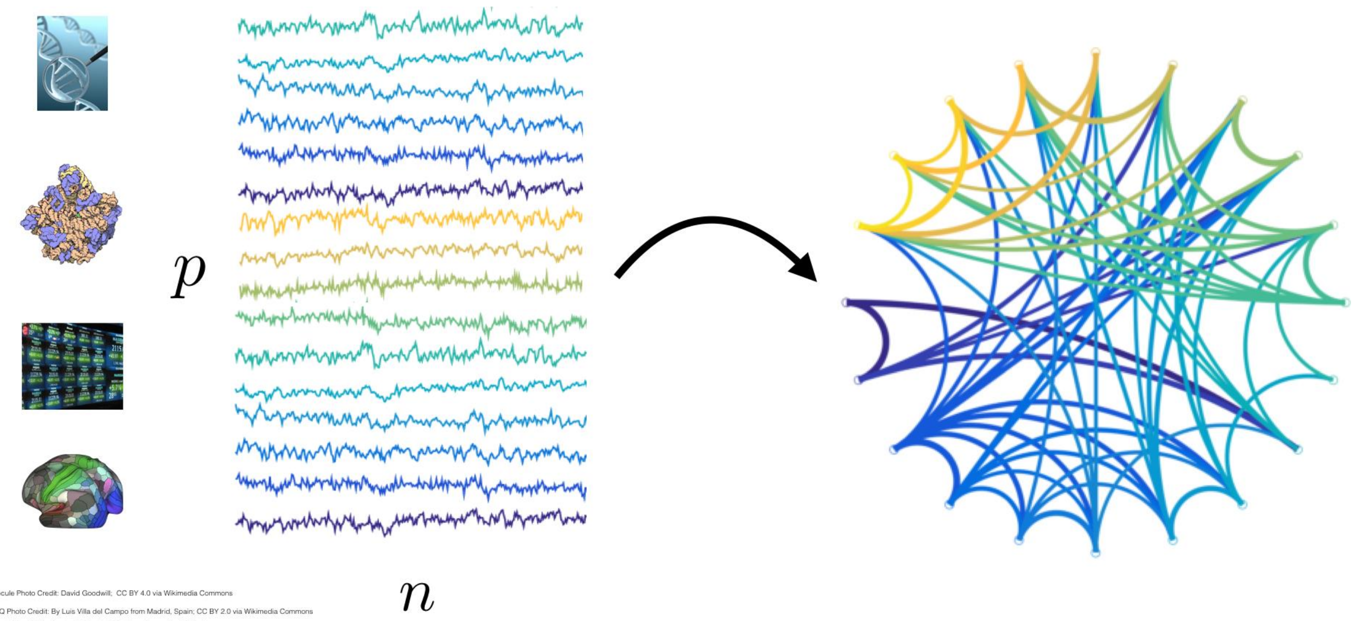
DIY – with grand unified framework





Mapping interconnections & change in capital markets

Information filtering networks to generate sparse probabilistic models (cf G-LASSO)
E.g. “de-noise” a correlation matrix
(Tomaso Aste & Tiziana Di Matteo)



Parsimonious interconnectedness models

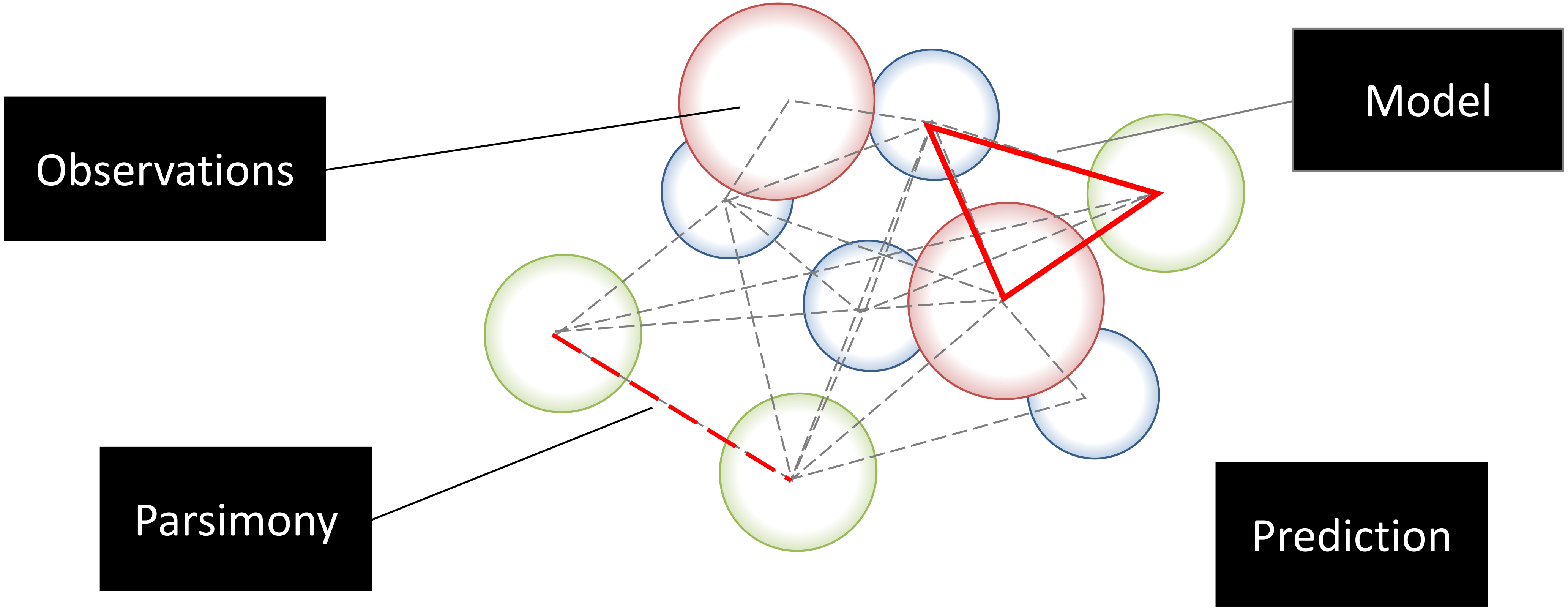
Problem

- CMSA requires quant measures for **interconnectedness of products** (assess, visualize)
- Desire model = MV PDF
- Public market data series: short & numerous
- Many connections in high dim’l space
- **Sparse structure learning** can find meaningful and parsimonious models, but slowly:
  - Constraint, score, regression based (ridge, lasso, elastic-net), decomposable models
  - Cf **graphical least absolute shrinkage & selection operator** – (G-LASSO) (L1 reglzn)

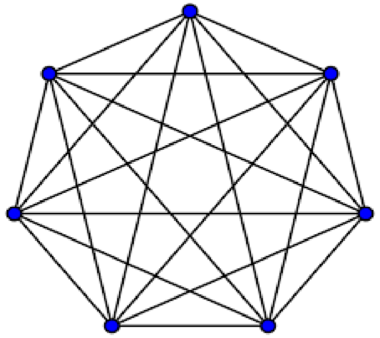
Solution

- **Information Filtering Networks** find **maximally filtered graph**, flavours:
  - *Max spanning tree* (MST)
  - *Planar* PMFG
  - *Triangulated* TMFG (efficient & decomposable)
  - LoGo = decomposable IFN + GMRF
- Trick: data are points
  - **Don’t**: start with full pdf, & discard (conditionally) independent variables
  - **Do**: start with “similar” vars & build geometric structures (clique forest) (“knowledge”)
- E.g. estimate **inverse covariance** of high-dim’l, noisy, short time-series
- Simplify the system of connections

Predictive modelling for a complex world

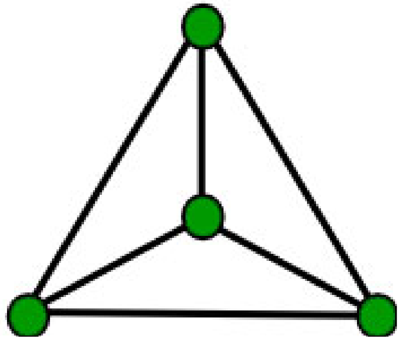


Graphs: complete, planar, chordal, tree



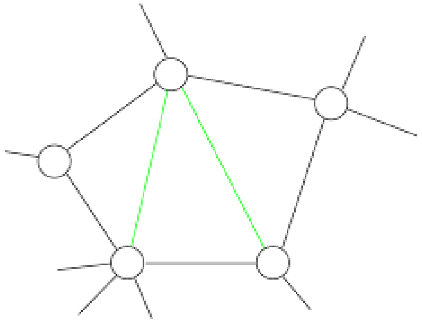
Complete

All nodes connected to all others – as in clique



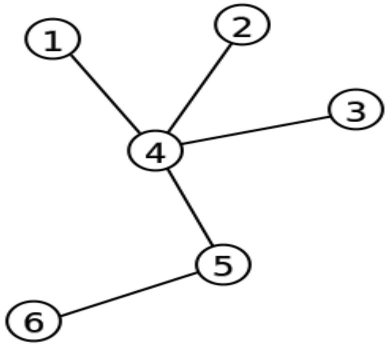
Planar

Can draw in the plane without any arcs crossing



Chordal

All cycles $\geq$ 3 have a chord



Tree

Any 2 vertices connected by exactly 1 path

Predictive modelling

- Predictive modelling

$$\overbrace{\mathbb{P}(B|A)}^{\text{Conditional probability}} = \frac{\overbrace{\mathbb{P}(A,B)}^{\text{Joint probability}}}{\mathbb{P}(A)}$$

- Conditional expectation

$$\mathbb{E}(Y|X=x) \qquad \text{(Discrete RV.)}$$
$$= \sum_y y\,\mathbb{P}(Y=y|X=x)$$

- Conditional entropy

$$\mathbb{H}(Y|X) = -\sum_{x,y} p(x,y)\ln p(y|x)$$

- Reduction of uncertainty on Y, given past X^-, discounting for past Y^-, is:

$$\mathbb{H}(Y|Y^-) - \mathbb{H}(Y|X^-,Y^-)$$
$$= \mathbb{TE}(X \rightarrow Y)$$

- **Transfer entropy**, for linear (MV Gsn) is **Granger causality**

Conditional dependency

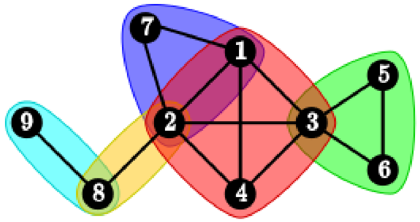
- Compare
  - Independent 
    $p(X, Y|\bar{Z}) = p(X|\bar{Z}) \times p(Y|\bar{Z})$
  - Dependent 
    $p(X, Y|\bar{Z}) \neq p(X|\bar{Z}) \times p(Y|\bar{Z})$
  - $\bar{Z} = Z \backslash \{X, Y\}$
- Conditional dependency
  - As hard as entire joint PDF ☹
  - Combinatoric complexity

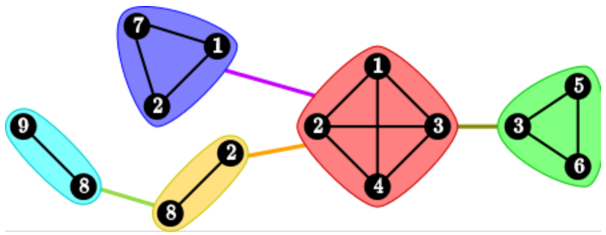
- Get inference structure from **information filtering network**
- Steps
  - Connect nodes that are close
    - Euclidean – correlated
    - Hyperbolic – mutual info ($\ln \rho$)
  - Maintain chordal property
  - Constrain clique size, planarity, info criteria
- Fast! $O(N)$; parallelizable $O(\ln N)$

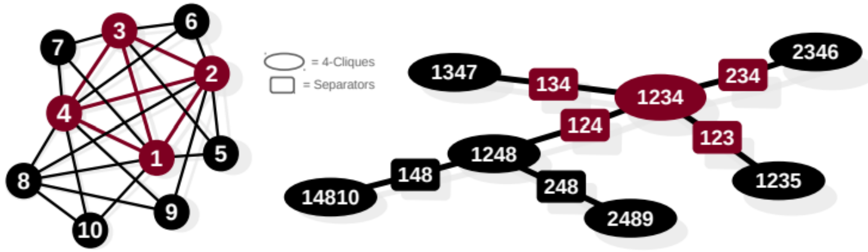
T. Aste, T. Di Matteo and S. T. Hyde, Complex networks on hyperbolic surfaces Physica A 346 (2005) 20-26.

M. Tumminello, T. Aste, T. Di Matteo, and R. N. Mantegna, “A tool for filtering information in complex systems” Proceedings of the National Academy of Sciences of the United States of America 102, 10421 (2005).

Chordal graphs



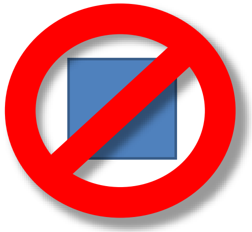




- **Chordal*** graphs have a recursive decomposition by **clique separators** into smaller subgraphs

  *Or **decomposable** or **triangulated**

- No squares!

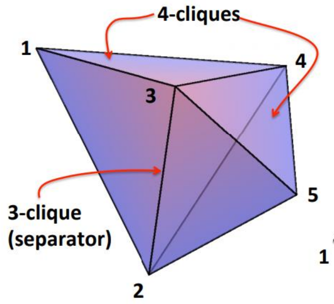


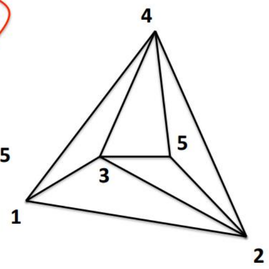
- Clique forests connected by separators
- Decomposable graphs can be parametrized by (ratios of) marginals

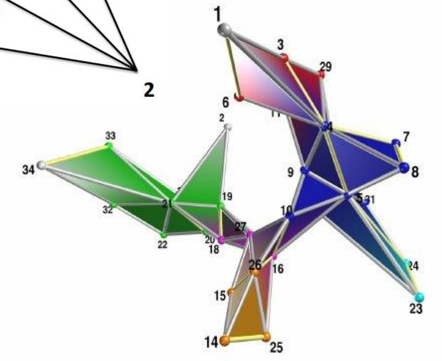
$$p(X) = \frac{\prod_c p(X_c)}{\prod_s p(X_s)^{(k_s-1)}}$$

Cliques (N)

Separators ($N-1$)







- Estimate joint pdf of system (numerous) from pdfs of cliques and separators (few)

Linear / Gaussian models

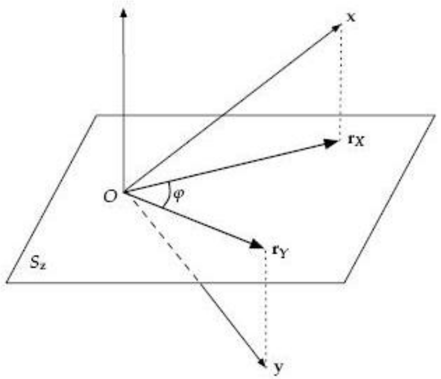
- **Multivariate normal**:

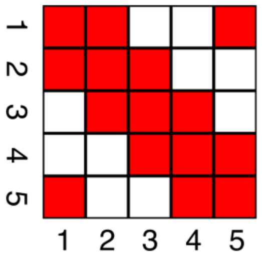
$$p(X) = \frac{1}{Z}\exp(-\sum_{i,j} X_i.J_{ij}.X_j)$$

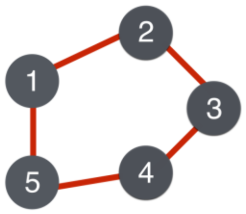
- Zero uncertain interactions iff RVs conditionally indep
- **Precision matrix** (PM) $J = \Sigma^{-1}$ is sparse, w’ IFN structure

- Sparse PM from *local* inversion of cov matrix over clique forest

$$J_{ij} = \sum_C \Sigma_C^{-1} - \sum_S (k_S - 1)\Sigma_S^{-1}$$



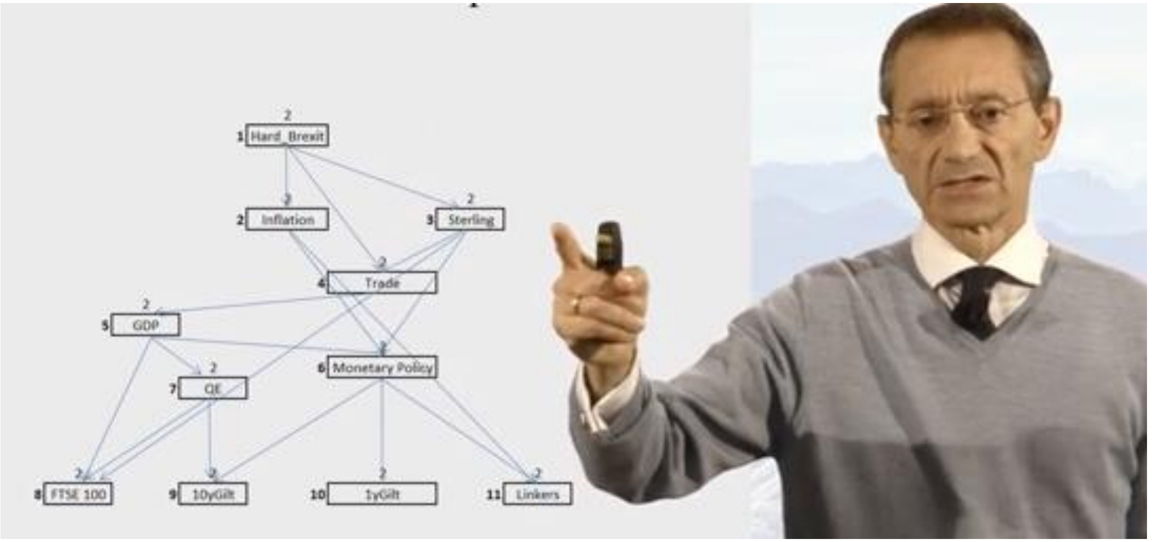




W. Barfuss, GP Massara, T Di Matteo & TA “Parsimonious modeling with Information Filtering Networks” Phys Rev E 94, 062306 (2016) https://arxiv.org/abs/1602.07349

Further reading

- **Information filtering**
  - Barfuss, Wolfram, Guido Previde Massara, T. Di Matteo, and Tomaso Aste. 2016. "Parsimonious Modeling with Information Filtering Networks." *Physical Review E* 94 (6). https://doi.org/10.1103/PhysRevE.94.062306.
  - https://vimeo.com/185463870 **Video**
  - http://bigdatafinance.eu/wp/wp-content/uploads/2017/07/Predictive-modelling-with-information-filtering-networks.pdf



Coherent stress testing

"Stress testing is in a statistical purgatory. We have some loss numbers, but who is to say whether we should be concerned about them?" Berkowitz's (1999)

Scary stress numbers – should we worry?

Stress testing with Bayesian nets

Problems

- Assess resilience of the financial system
- ST - incoherent story
- Inputs
  - Scenarios
    - Macroeconomic aggregates
    - Severe. Likely?
  - Backward-looking models - historical data
  - ~~Domain knowledge (incl. causal)~~
- Complex
- Outputs
  - Interpret & understand
  - Aggregate - diversification / amplification

Solution

- BN = intuitive, transparent structure
  - Visual ; understandable
  - BN = model (assumptions)
  - Parsimonous factorization of PDF
- Aggregate sources of info
  - historical, market prices, expert opinions etc
- Updated with new info
- Rigorous
- Holistic
  - credit, market, liquidity risks
- ~ Structural equation models (SEMs)

Risk propagation – BN variables

Root events = triggers e.g. break up of Euro

Connecting nodes = transmission channels e.g. failure of FI, actions of CB

Macro-financial variables e.g. GDP growth, inflation, market sentiment

Representative market indices e.g. bond yields, oil, TSX index

Granular market indices e.g. non-BM bond maturities, stock prices etc.

Cognitive Ease / Coherent

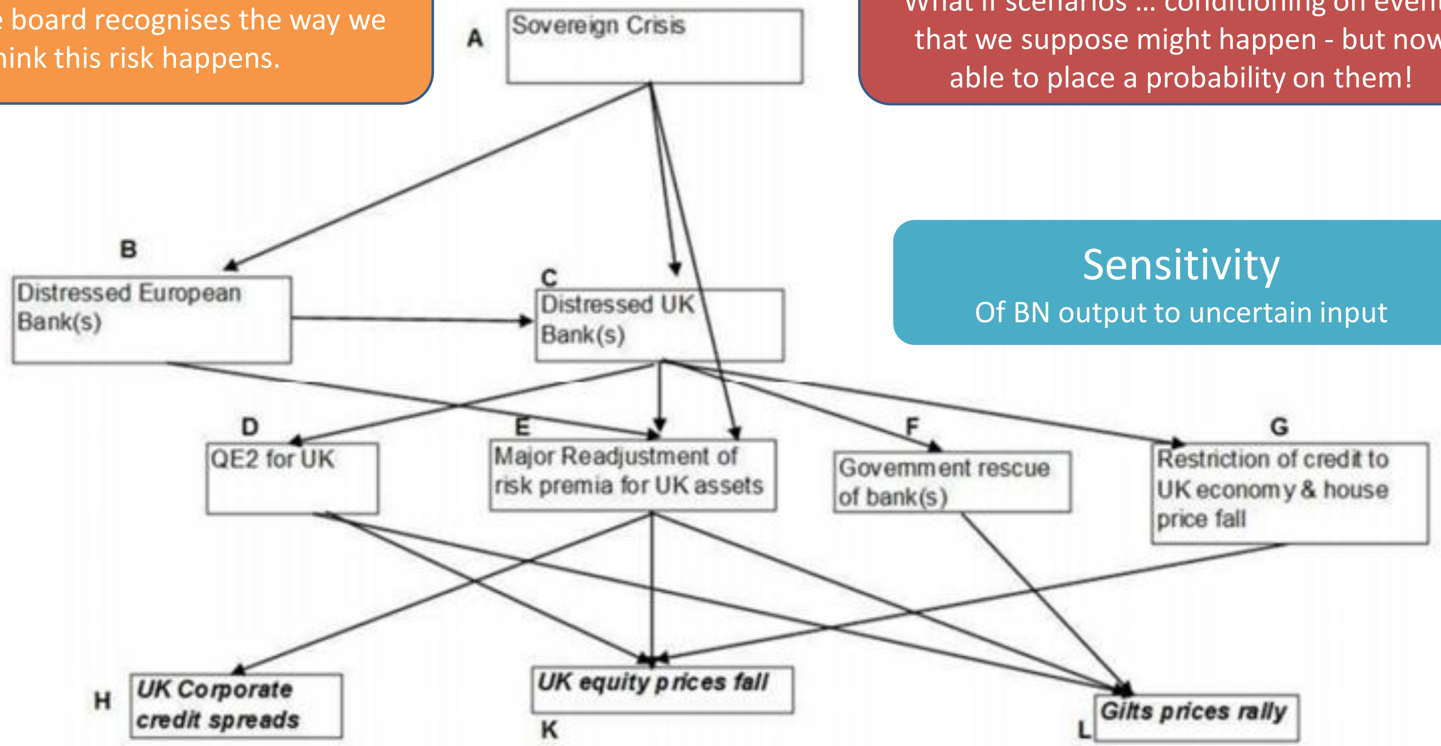
Check the board recognises the way we think this risk happens.

Stress tests

What if scenarios … conditioning on events that we suppose might happen - but now able to place a probability on them!

Sensitivity

Of BN output to uncertain input



PDF

Produce a PDF for key factors based on aggregating hard and soft data.

Reverse ST

Condition on a bad event happening and see what the world would need to look like to make it so.

Further reading

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- Rebonato, Riccardo, and Alexander Denev. “Coherent Asset Allocation and Diversification in the Presence of Stress Events.” SSRN Scholarly Paper. Rochester, NY: Social Science Research Network, April 27, 2011. https://papers.ssrn.com/abstract=1824207.

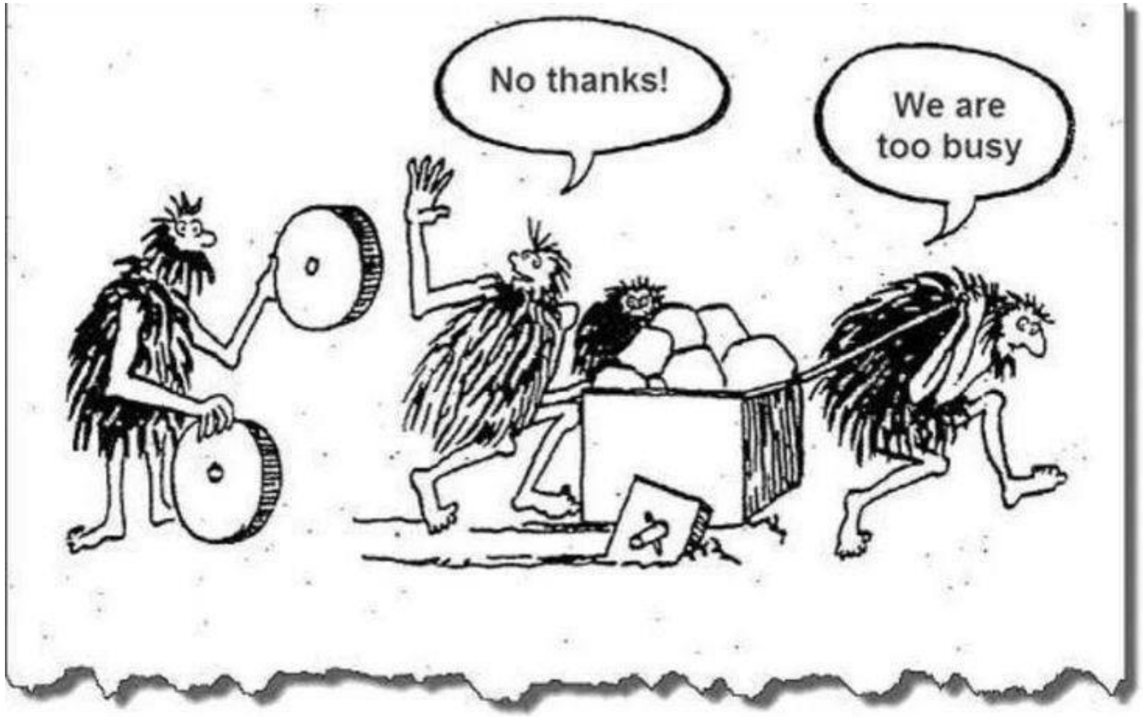
Causal inference

… I see no greater impediment to scientific progress than the prevailing practice of focusing all our mathematical resources on probabilistic and statistical inferences while leaving causal considerations to the mercy of intuition and good judgment.

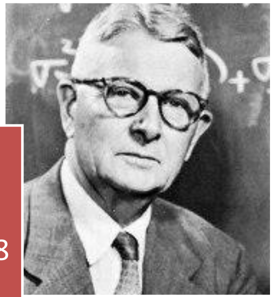
-- Pearl, 1999

To know, is to know the final cause.
-- Aristotle

When I was growing up, we didn't have DAGs because we was too PO
-- Tim Simmons



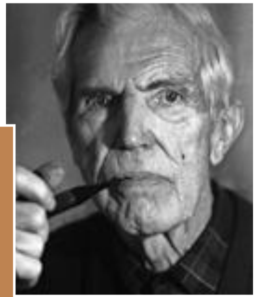
Innovators – causal inference



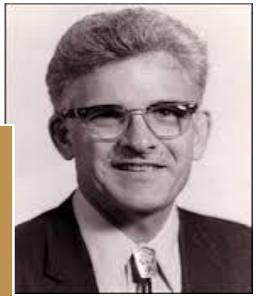
Wright
- 1889-1988

Neyman
- 1894-1981

Burks
- 1902-1943



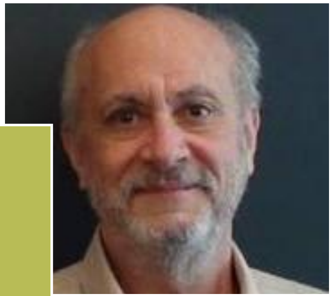
Haavelmo
- 1911 – 1999



Duncan
- 1921-2004

Granger
- 1934-2009

Pearl
- 1936-



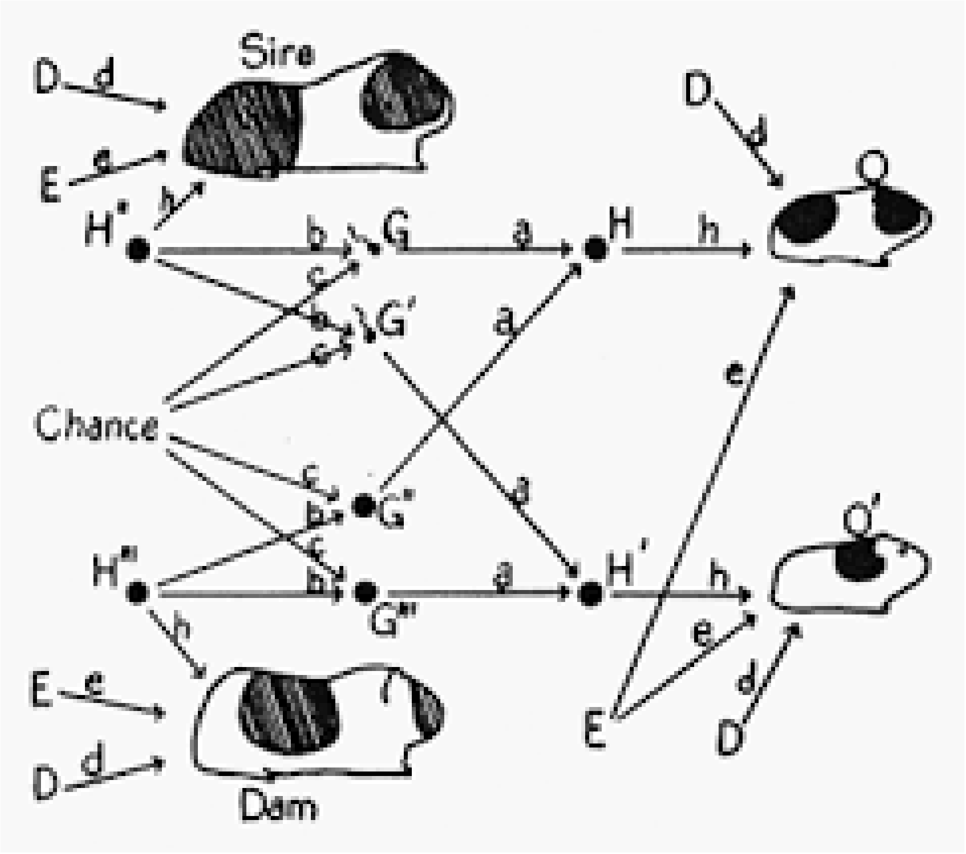
Rubin
- 1943-

Heckman
- 1944-

Athey
- 1970-

Causal inference – science of cause & effect

- A **causal model**
  - predicts behaviour of a system.
    - probability, of **counterfactual** claims about the system;
    - effects of **interventions**
    - probabilistic dependence or independence of variables included in the model.
  - inverse of these inferences:
    - if we have observed
      - probabilistic correlations among variables
      - outcomes of experimental interventions
    - determine which causal models are consistent with these observations
- Wright
  - **path analysis** 1921
  - (Unblocked) paths are a channels along which information (correlation) can flow, and so we add across channels



Counterfactual question: If X would have been X’, what would be the value of Y?

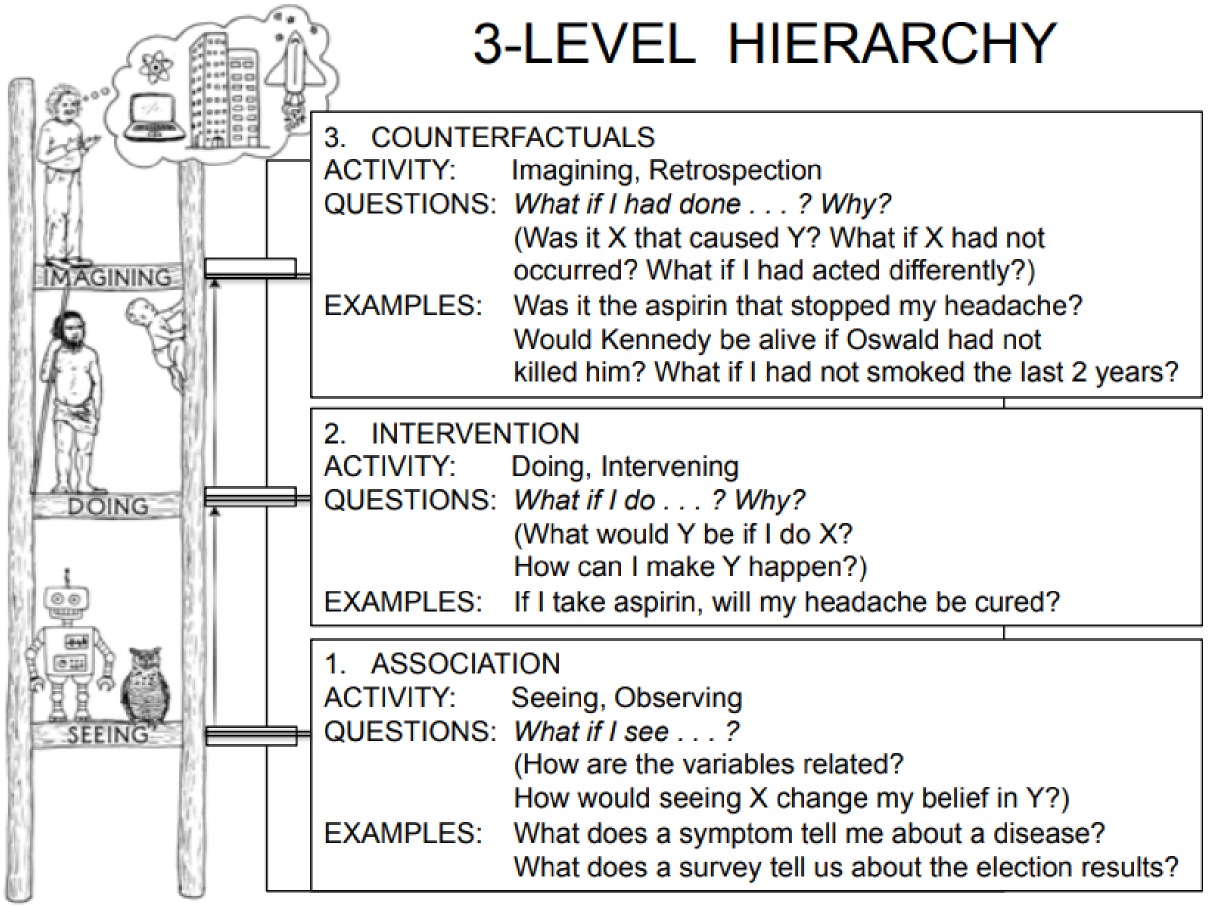
Interventionist question: If X is changed to X’, what will be the value of Y?

- Experiments, Reinforcement learning, Contextual bandits.

Correlation question: How well can X predict Y?

- Machine learning, Statistical estimation.

See. Do. Imagine.



Source: http://causality.cs.ucla.edu/blog/wp-content/uploads/2017/12/nips-dec2017-bw.pdf

Estimating the effect of policies on outcomes

- *However, in many cases, [randomized]* ***experiments remain difficult or impossible to implement****, for financial, political, or ethical reasons, …. Thus, a large share of the empirical work in economics about policy questions relies on* ***observational data****—that is, data where policies were determined in a way other than through random assignment. Drawing inferences about the causal effect of a policy from observational data is quite challenging*

  – Athey & Imbens.

- *We then briefly discuss some new developments in the machine learning literature, which focus on the* ***combination of predictive methods and causal questions****. We argue that machine learning methods hold great promise for* ***improving the credibility of policy evaluation****, … Overall, this article focuses on recent developments in econometrics that may be useful for researchers interested in* ***estimating the effect of policies on outcomes****.*

  – Athey & Imbens

Further reading

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- Kalisch, Markus, Alain Hauser, Martin Maechler, Diego Colombo, Doris Entner, Patrik Hoyer, Antti Hyttinen, et al. 2018. *Pcalg: Methods for Graphical Models and Causal Inference* (version 2.6-0). https://CRAN.R-project.org/package=pcalg.
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Software

Software for building probabilistic graphical and or causal models

Software

probabilistic programming & graphical models

*Commercial

Pgmpy

- Python library for working with Probabilistic Graphical Models.

BNLearn

- R package for learning the graphical structure of Bayesian networks, estimate their parameters and perform some useful inference.

Infer.NET

- Framework for running Bayesian inference in GMs
- It can also be used for probabilistic programming.
- Recently open-sourced by MSFT
- Script with F#

Stan

- Probabilistic programming language for statistical inference written in C++.
- Script with PyStan & Rstan.

PyMC3

- Prob prog package for Python
- Fit Bayesian models: **Markov chain Monte Carlo** (MCMC) and **variational inference** (VI).
- Used by **Quantopian**.
- Built using **Theano**

Edward

- Python library for probabilistic modeling & inference,
- Built on **TensorFlow**.

Skggm

- Gaussian graphical models in scikit-learn

DoWhy

- Python library to estimate causal effects.; based on a unified language for causal inference, combining causal graphical models and potential outcomes frameworks.

BayesiaLab*

- Bayesia develops AI software for ML, knowledge modeling, analytics, simulation and optimization.

Avis Nigra*

- Avis Nigra offers expertise in scenario-based risk management by constructing relevant and tractable models of risks that are not accessible by statistics alone.

Conclusions

Probabilistic graphical models as a tool for

- sparse interconnectedness models from historical market data and
- coherent stress tests for financial system resilience assessment

Conclusions

Parsimonious interconnectivity

- Aste, Di Matteo et al
- **Information filtering networks**
- Graphical representation of strongest dependencies e.g. precision matrix J
- Eliminating weak dependences as hard as full precision matrix ☹
- Construct quickly, sparse matrix as clique forest
- Chordal graph – pdf factorizes ☺
- Sparse regression – prediction
- Deduce causal relationships (output)

Coherent stress tests

- Rebonato, Denev
- Should we worry?
- Causation central (input)
- Framework for quant stories
- Combine frequentist & subjective uncertainty
- Intuitive, understandable (challengeable) by executives
- Sensitivity analysis - which inputs
- Produce pdfs for market indices driving financial system

The End

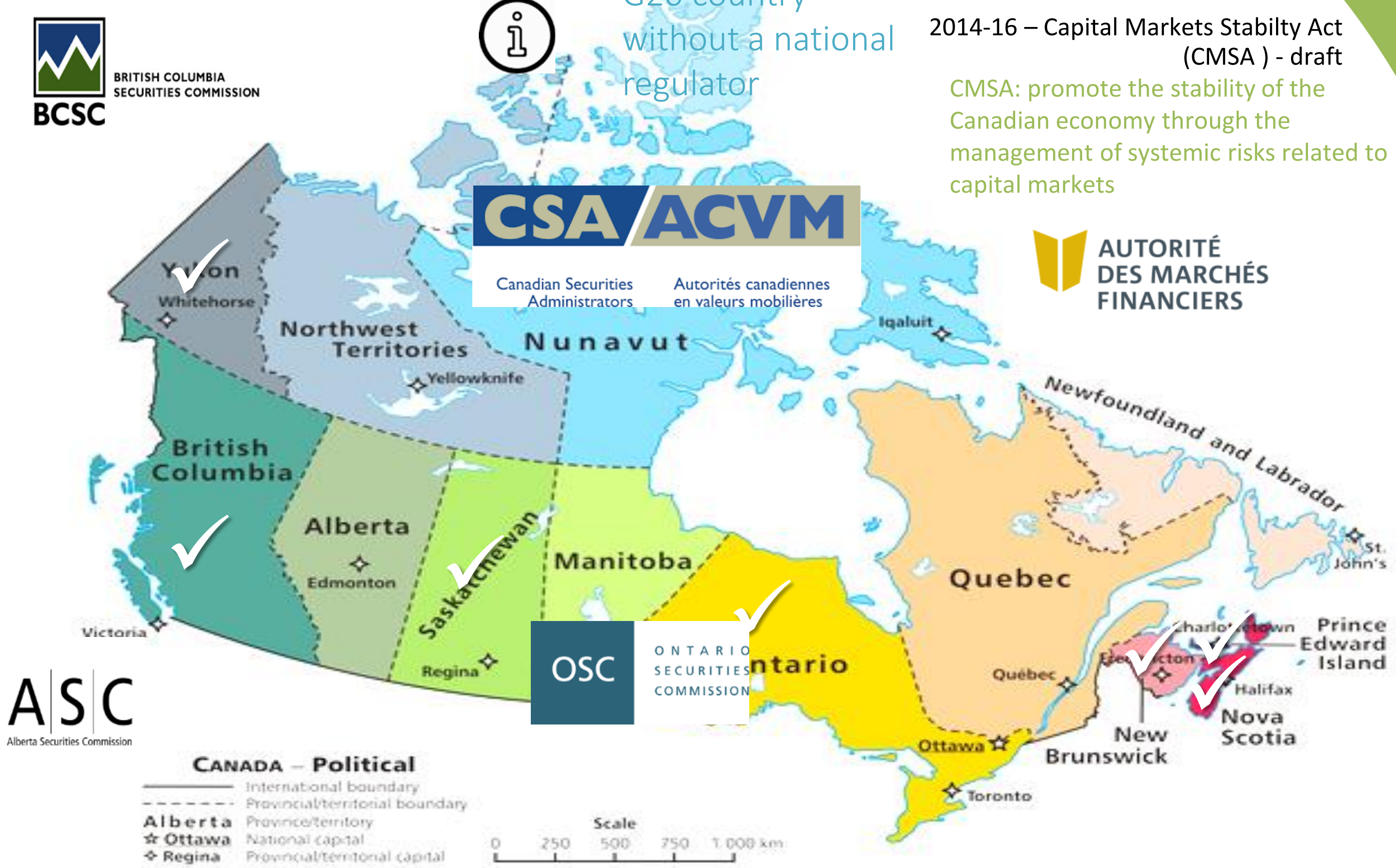
Thank you for listening

Appendix: Canadian context

History, geography of the Canadian regulatory landscape

Capital Markets Regulatory Authority (CMRA)

Canada is the only G20 country without a national regulator



2009 - federal finance minister Jim Flaherty

2011 - SCC reference: national securities regulator was unconstitutional ☹

2013 – AIP: BC, ON, Canada

2014 – MOA cooperative capital markets regulatory system +SK, NB + PEI (Sept)

2014-16 – Capital Markets Stabilty Act (CMSA) - draft

CMSA: promote the stability of the Canadian economy through the management of systemic risks related to capital markets

2015 + YK

AUTORITÉ DES MARCHÉS FINANCIERS

2015 CMAIO

2016 – Board of directors + Chief Regulator + Systemic risk team

2017 – QCA

- CCMR reg regime unconstitutional (council of ministers)
- CMSA is OK

2018 April – SCC hearing

- +NS

2018 Dec – SCC verdict ☺

☺

2020 - Launch

"The preservation of capital markets and the maintenance of Canada's financial stability ... do not justify a wholesale takeover of the regulation of the securities industry"

CCMR(S) – Cooperative Capital Markets Regulatory (System) (2014)
CSTO – Canadian Securities Transition Office (2009)
CMAIO – Capital Markets Authority Implementation Organization (2015)
CMRA – Capital Markets Regulatory Authority (2020)
CMA – Capital Markets Act ()
CMSA – Capital Markets Stability Act (2014-16)

http://csto-btcvm.ca/home.aspx
https://en.wikipedia.org/wiki/Reference_re_Pan%E2%80%91Canadian_Securities_Regulation

CANADIAN REGULATORY LANDSCAPE