AI/ML in Finance: Is it just another bubble?
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Continual Learning, Reasoning and Explainable AI through Knowledge Extraction from Deep Networks

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The AI revolution...

It is not just another bubble:

Big Data a (valuable) fact of life

Record venture investments of $9.3B in the USA alone in AI start ups (AI Business, 2019)

But it is seriously hyped:

AI adoption still low (McKinsey, 2018)

AI revolution mainly due to...

… deep learning (a form of ML)

Very nice original idea (deep belief nets, semi-supervised learning) then highly engineered into systems that work in practice using *backprop*

Very successful/state-of-the-art at image recognition, speech/audio analysis, games, language modeling and translation, and to some extent question answering and video understanding

Brain/Mind dichotomy?

Symbolic AI: a symbol system has all that is needed for general intelligence

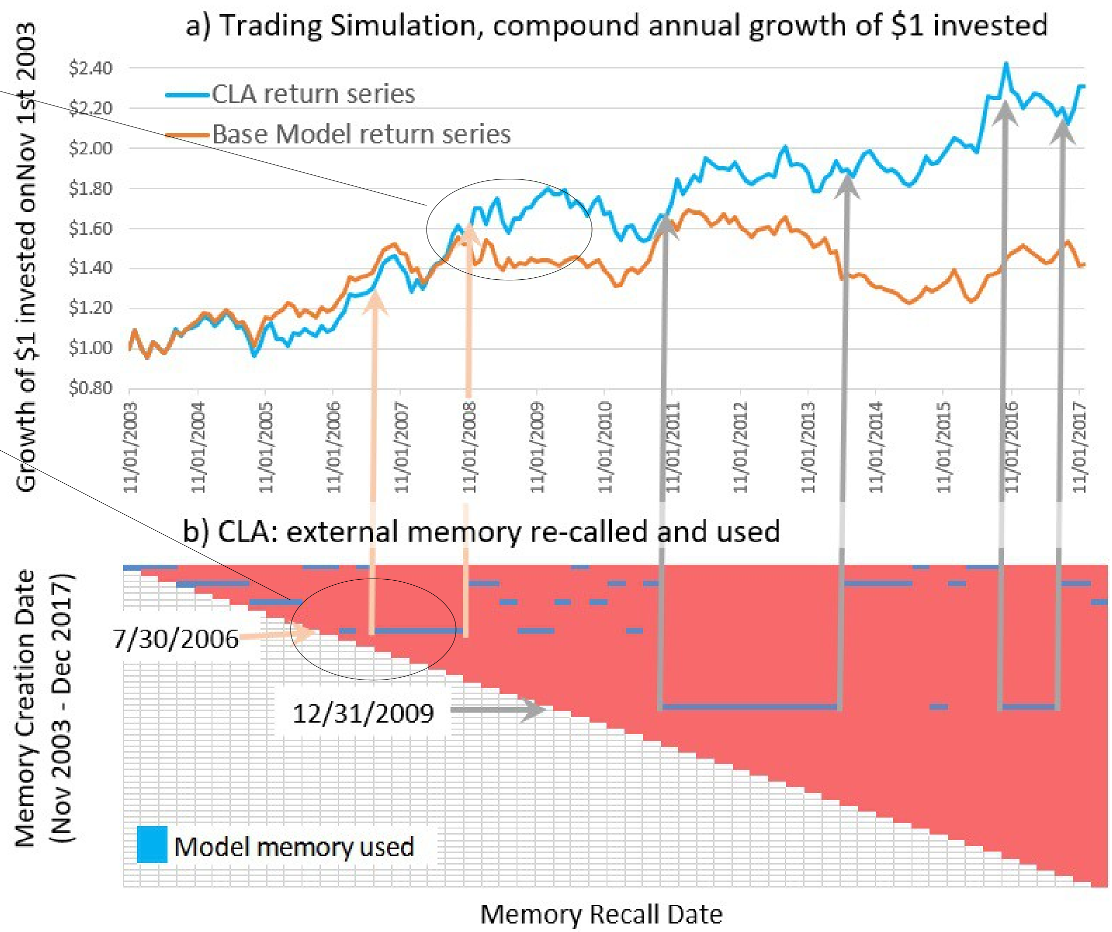
Sub-symbolic AI: intelligence emerges from the brain (neural networks)

Perhaps more useful than debating symbols vs. neurons (both are needed c.f. neural-symbolic systems) is the question: localist or distributed AI?

Continual Learning Augmentation

Lehman Brothers 2008

Quant Quake?



Time series trained by distributed neural nets

Memory recall explained by localist (if-then) rules

D. Philps, T. Weyde, A. d'Avila Garcez, R. Batchelor. Continual Learning Augmented Investment Decisions. NeurIPS 2018 Workshop on AI in Finance, Montreal, Dec 2018

Neural-Symbolic AI

Systems that learn from data but also reason about what has been learned (data + rules)

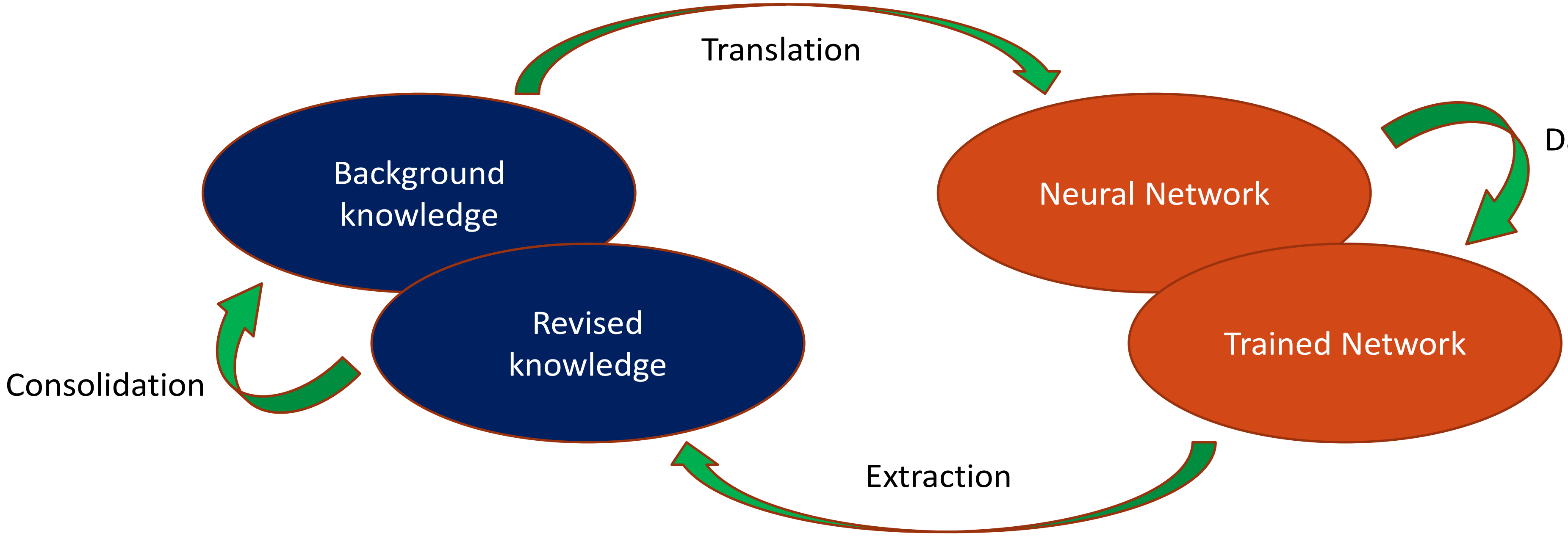
Research since late 1990s c.f. www.neural-symbolic.org now applicable in practice

Combines neural networks with (rule-based) symbolic AI to achieve reasoning and explainable AI

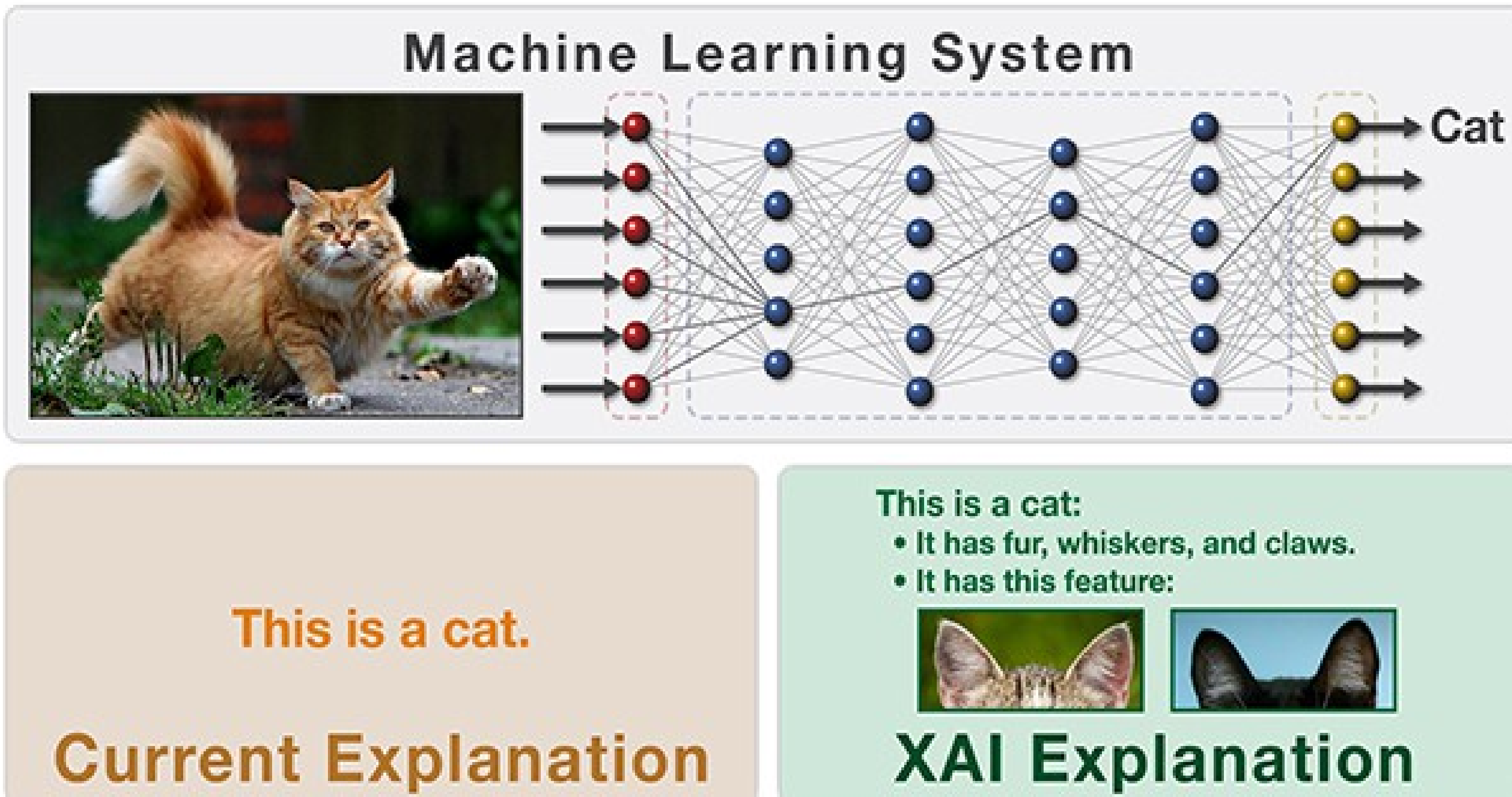
Taking advantage of data-driven ML and knowledge-based AI (e.g. logical rules)

e.g. self-driving cars: 10 billion miles of driving data (Waymo) but there is also the highway code!

Neural-Symbolic Cycle



Different forms of explanation e.g. DARPA's Explainable AI (XAI)



- XAI = Interpretable ML
- Explanation = knowledge extraction, not XAI

Practical Examples

Consumer protection (collaboration with Playtech plc)

- Transaction data + regulatory framework
- Predict whether a player might be at risk of harm and should take a break for a period of time

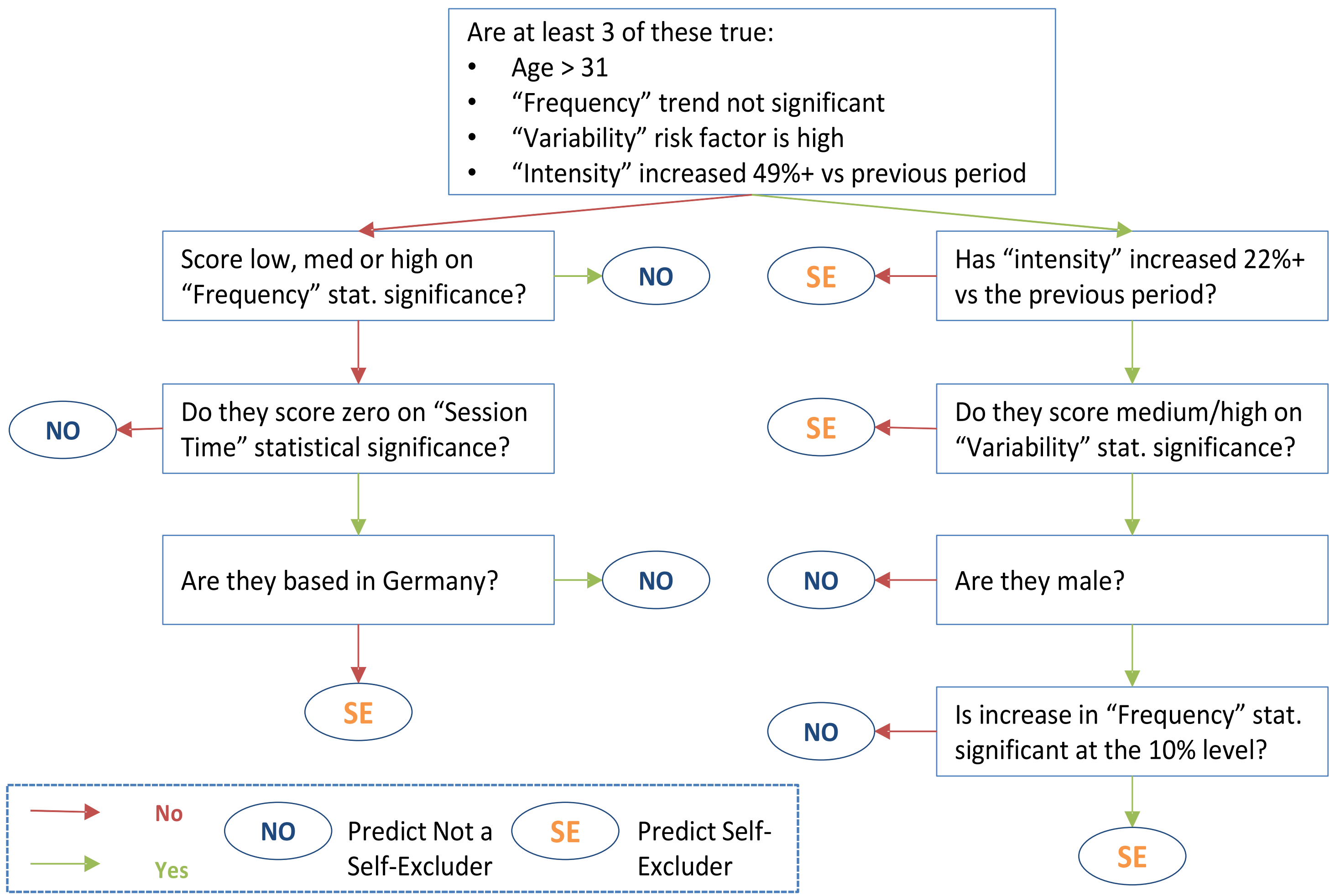
Anti money laundering (collaboration with Kindred)

- Also a case of data + rules (e.g. KYC)
- Data imbalance (matters a lot in practice); credit card fraud another well-known example
- Rules can help adjust and understand relationships between false positive and false negative cases

Collaboration with Playtech on XAI

- Neural net or random forest give a higher accuracy than Bayesian net or regression model
- Predict self-exclude based on transaction data: frequency of play, betting intensity, variation, ratio of night play, etc.
- Self-exclusion data used as a proxy for harm
- Query the black box to extract a decision tree for explanation or to improve the prediction

Knowledge Extraction



C. Percy, A. S. d'Avila Garcez, S. Dragicevic, M. Franca, G. Slabaugh and T. Weyde. The Need for Knowledge Extraction: Understanding Harmful Gambling Behavior with Neural Networks, In Proc. ECAI 2016, The Hague, September 2016.

For every complex problem there is an answer that is clear, simple, and wrong

H. L. Mencken

Measuring the fidelity of knowledge extracted to the original black box ML is key!

So, Knowledge Extraction is needed

From a regulatory perspective,

But also to help improve system performance (learn from your mistakes!), and

increase consumer confidence (in future, consumers will choose the systems that they can trust), and

for data/energy efficiency (will Waymo self-driving car require 10 billion miles to learn to drive in London?)

Not to mention Ethics of AI (c.f. *Are they male?*)

Human in the loop? Caution!

The AI system won't be there just to support the humans; the system will be making the decisions...

In fact some systems are already doing so (c.f. The Digital Poorhouse, J. Weisberg)

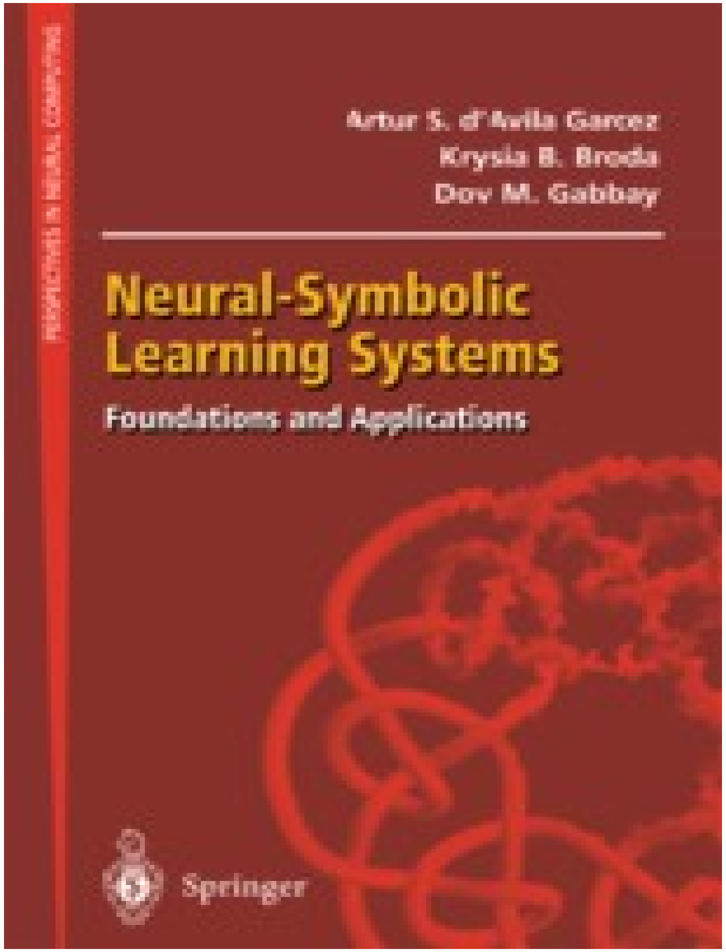
Humans cannot process Big Data; the human's decisions are biased by *data triage* made by the system

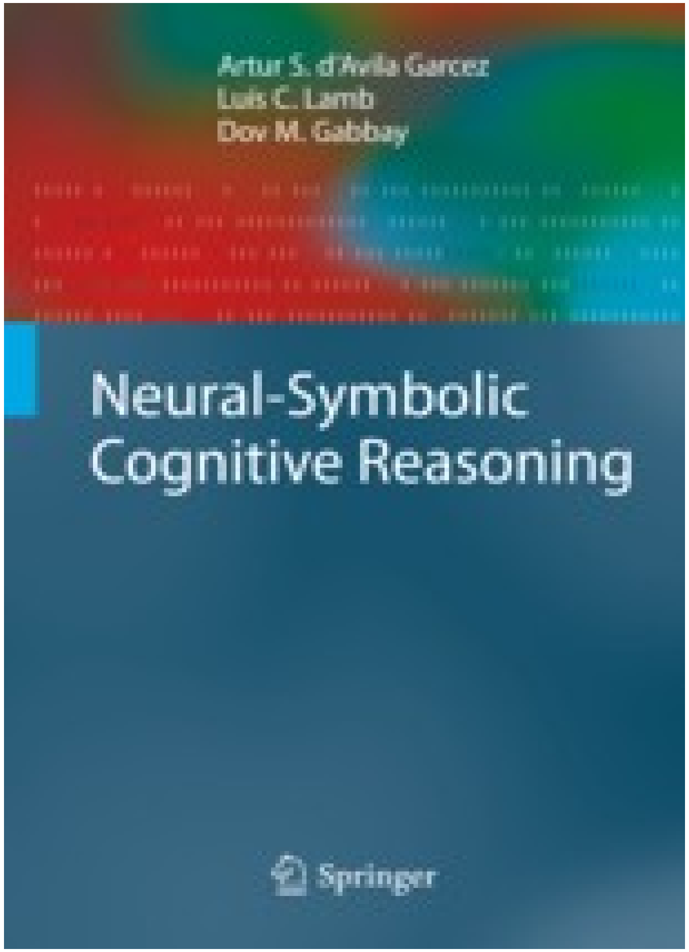
Therefore, keeping the human in the loop does not solve the black box problem of ML (neither will it address the GDPR right to an explanation)

Neural-Symbolic AI (Cont.)

- Neural networks provide the machinery for effective learning and computation
- Perception alone is insufficient: AI needs reasoning, explanation and transfer
- Rich knowledge representation models: nonmonotonic, relational (with variables), recursion, time, uncertainty…
- Neural-symbolic computing: neural networks with a logical (modular) structure

For more information…





Knowledge Extraction techniques

- Decision trees from feedforward networks
- Graphs from recurrent networks
- Counterfactual explanations (local explanations of an instance/case, as opposed to global explanations of an entire ML model)

  E.g.: if your salary were to increase by 20%, you would have been successful with the application for credit all else being equal

A. White and A. d'Avila Garcez, Measurable Counterfactual Local Explanations for Any Classifier https://arxiv.org/pdf/1908.03020.pdf

The need for a measure of fidelity

- A guarantee that the explanation extracted reflects the behavior/semantics of the neural network
- Sound/complete extraction may be computationally intractable (guarantees in the limit only)
- In practice, efficient extraction may be unsound (and work more like a learning algorithm)
- Soundness/completeness needed if neural net is used for decision making in a safety-critical domain
- This line of research is very relevant to recent efforts on verification of neural networks (EPSRC project proposal in collaboration with JP Morgan)

Knowledge extraction enables...

- Continual learning
- Reasoning (about what has been learned)
- Explanation

Knowledge Extraction algorithms

Pedagogical: treat network as an oracle to query input/output patterns

Decompositional: inspect the internal structure of the network

Eclectic: consider doing both of the above

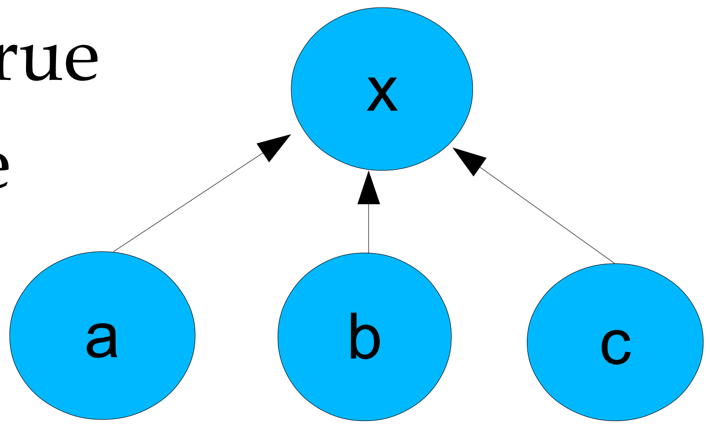
Reasoning (1)

- MofN: neural nets very good at learning/ representing MofN rules:

  If 2 of (a,b,c) are True then x is True

  If 1 of (a,b) is False then x is True

  etc.

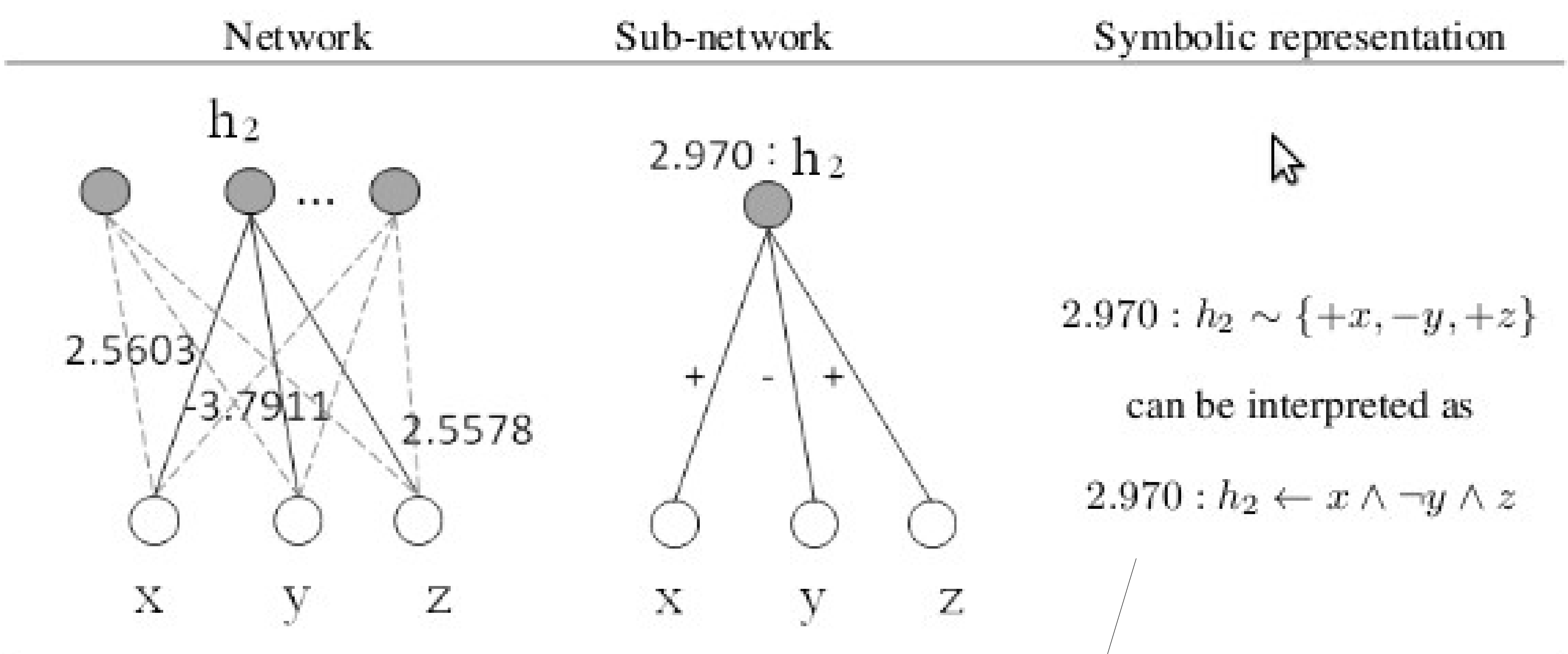


Knowledge-based artificial neural networks, G. Towell and J. Shavlik, AIJ, 1994

Symbolic knowledge extraction from trained neural networks: A sound approach, A. d'Avila Garcez, K. Broda, D. Gabbay, AIJ, 2001.

Reasoning (2)

Knowledge extraction from RBMs (building block of Hinton's deep networks)



Each rule has a confidence value ∑||w||/n

Probabilistic MofN

We can improve the accuracy of rules extracted from RBMs by extracting MofN rules

Search values for M given extracted rules, e.g. M=0,1,2,3 in

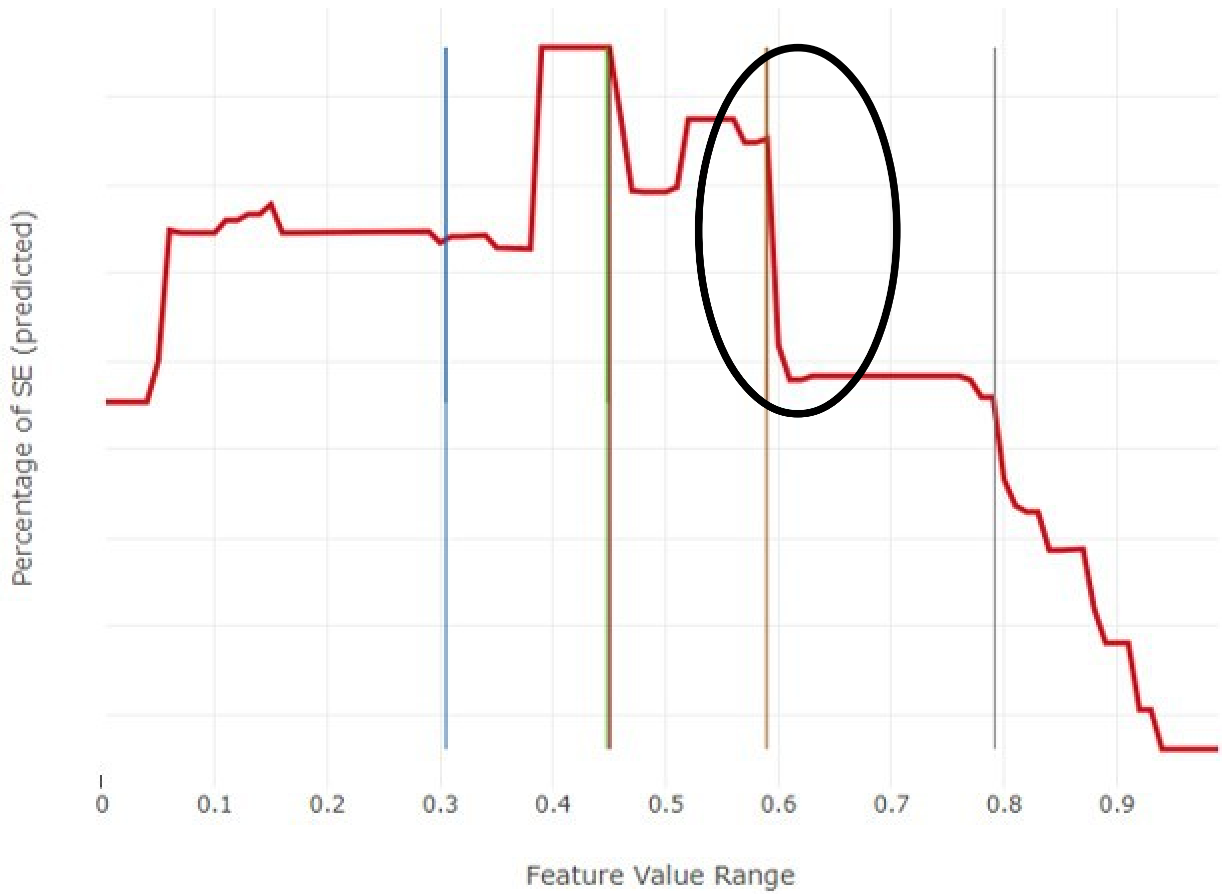
$$2.970 : h_2 \leftarrow \text{M of } \{x,\sim y,z\}$$

Simon Odense and Artur S. d'Avila Garcez. Extracting M of N Rules from Restricted Boltzmann Machines, ICANN 2017.

S. Tran and A. S. d'Avila Garcez. Deep Logic Networks: Inserting and Extracting Knowledge from Deep Belief Networks. IEEE Transactions NNLS, Nov, 2016

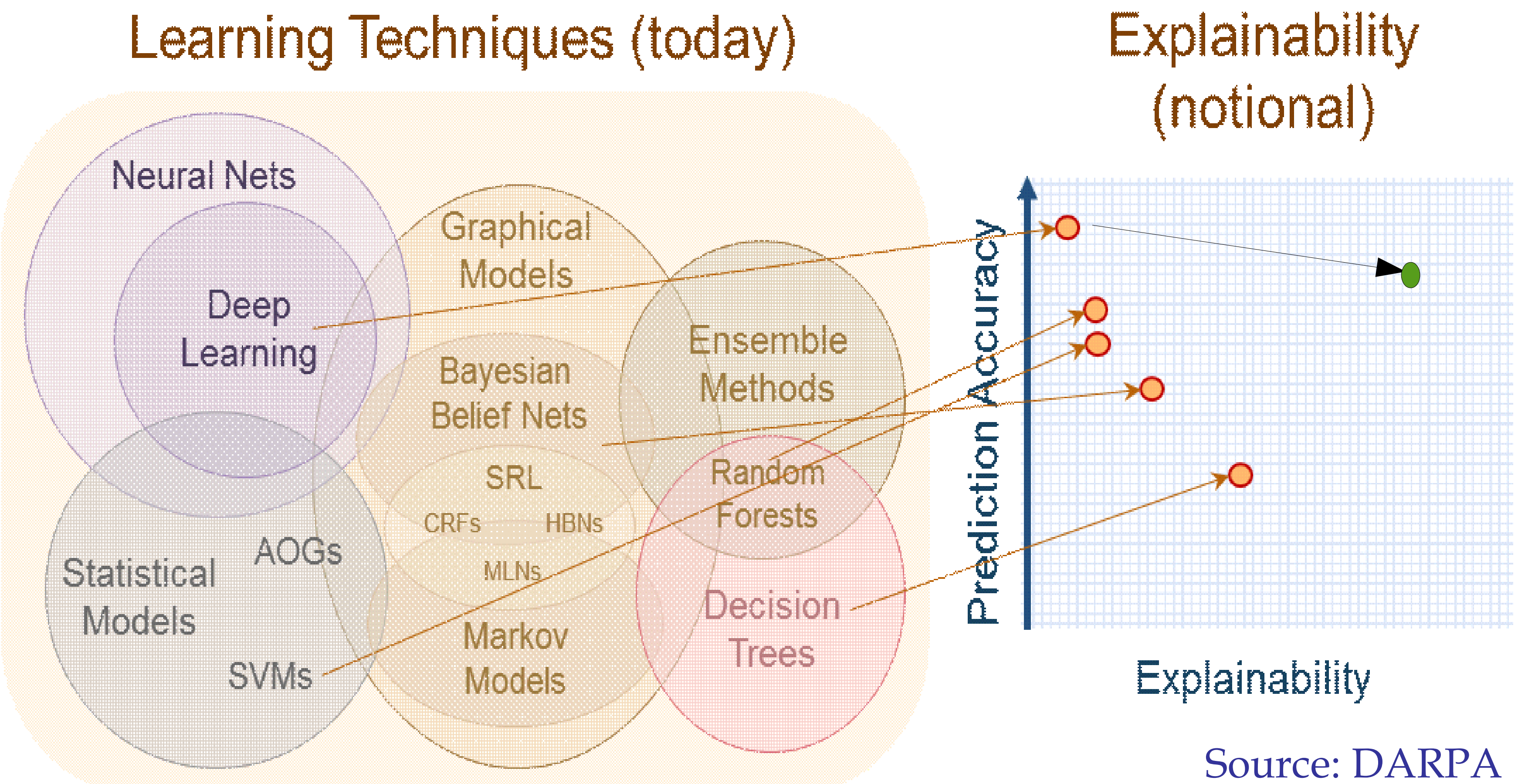
Intervention

Make this sharp drop smoother?



Different interventions by different stakeholders (e.g. hospital or insurance company)

Explainable AI = ML + KR



Source: DARPA

Challenges

- If you have a neural-symbolic system then you can control for modularity
- But if you don't then extraction of knowledge (beyond heat maps) from large-scale networks (e.g. densenets 169 layers) is a big challenge computationally
- Extraction of FOL from neural nets at different levels of abstraction (seems to require modularity)
- Alternative: try to explain an instance instead of the entire model, e.g. DeepMind's long-term sacrifice in chess...

The City Data Science Institute

https://www.city-data-science-institute.com/

- Machine Learning (Computer Science)
- Computer Vision (Engineering)
- Complex Networks (Mathematics)
- Data Visualization (Computer Science)
- Finance (CASS Business School)
- Healthcare (School of Health Science)
- Economics (School of Arts and Social Sciences)
- Ethics (The City Law School)

Partners: NHS, BBC, British Library, Imperial College Data Science, Societe Generale, Chinese Academy of Sciences, Delta Capita, Telefonica Alpha...

Conclusion: Neural-Symbolic Systems

To study the statistical nature of learning and the logical nature of reasoning.

To provide a unifying foundation for robust learning and efficient reasoning.

To develop effective computational systems for AI applications.

Thank you!