

Algorithms in Platform Economy: Legal Implications

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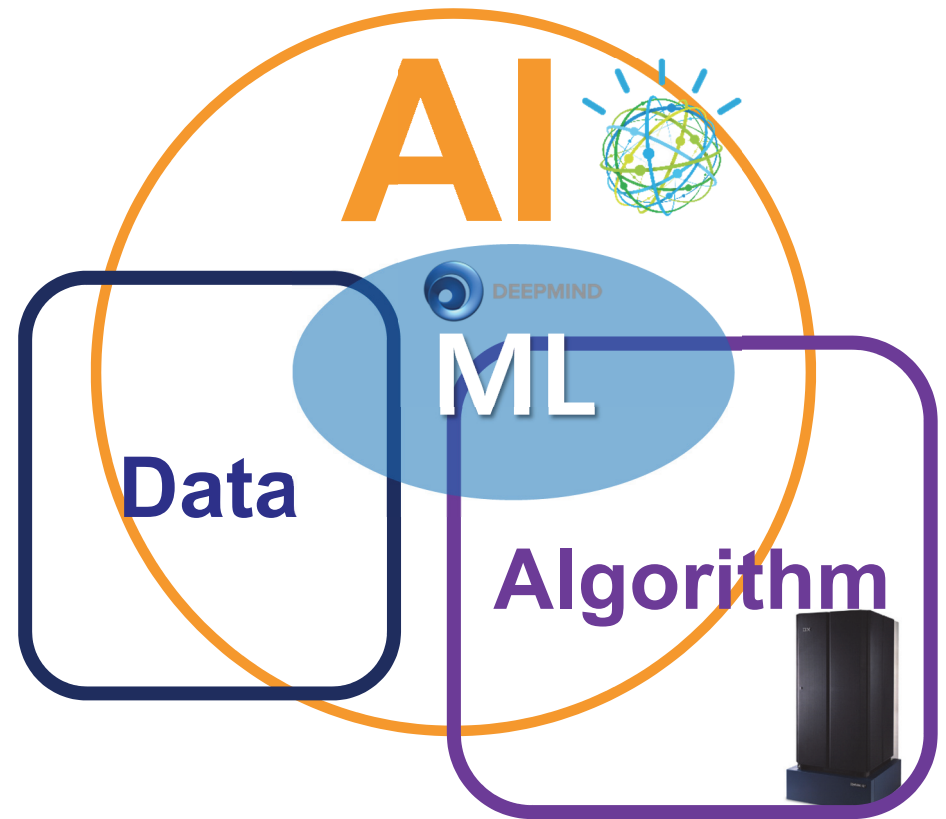
- Prior to the beginning: AI, data, and algorithm
- Not all algorithms are equal. There are many variations.
- Understandings of Algorithms: friends or foes?
 - ✓ Nature of Algorithms
- Legal Issues around Algorithms
 - ✓ Transparency and Accountability
 - ✓ Manageability: a suggestion
 - ✓ Public use vs. Private use
- Discussions

AI, Data, and Alg (Algorithm)

Algorithm \neq AI

Algorithm $\not\subset$ AI

Alg \cap Data $\approx \emptyset$



AI, Data, and Alg (continued)

- invisible biases engrained in alg? (Raymond et al., 2017)
 - ✓ e.g.) predictive policing (Brennan, 2015); accident case of self-driving vehicle – murder vs. manslaughter?; algorithmic censorship, etc.
 - ✓ not a problem of algorithm; but a problem of data

But, some alg (esp. ML) are heavily data-dependent → in fact, it is meaningless to distinguish alg from data

*Why your navigation works so well?
(most time)*



*When your navigation seems stupid?
(sometimes)*

Algorithm Typology

Optimization-oriented

- Algorithms (in a narrow sense)
 - ✓ Simplex algorithm
 - ✓ Convex optimization algorithms
 - ✓ Branch-&-bound algorithms
- Meta Heuristics
 - ✓ Genetic algorithms & swarm optimization algorithms
 - ✓ Search methods: Tabu search, Simulated annealing, etc.
 - ✓ Neural networks

Classification-oriented

- Regression-like
 - ✓ Linear, non-linear regressions
 - Logistic regression
 - ✓ CART(Classification and Regression Tree)
- Kernel-base methods
- Clustering methods
- Learning-oriented(data-driven)
 - ✓ Monte Carlo simulation basis
 - ✓ Neural networks

Algorithm Typology: more dimensions

Supervised

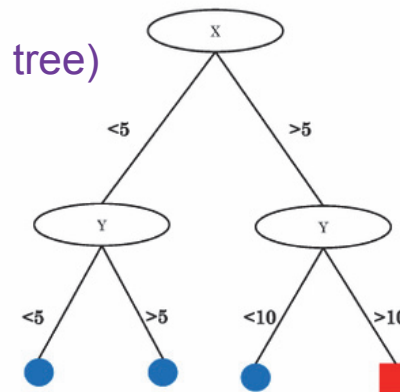
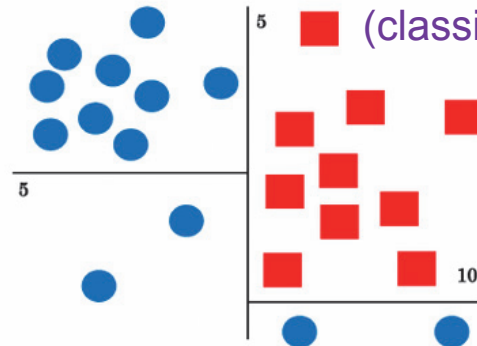
- Regression-like
 - ✓ linear, nonlinear, logistic, ...
 - ✓ generalized additive model: CART, PRIM, MARS, ...
- Kernel-base
 - ✓ SVM(Support Vector Machine)
- Neural Networks
 - ✓ data-driven methods

Non-supervised

- Clustering algorithms
 - ✓ data mining (in a narrow sense)
 - ✓ to find patterns in unstructured data set
- PCA-like algorithms
- non-supervised learning \neq self-reinforce learning
 - Self-reinforcing CNN (eg AlphaGo) belongs to supervised learning

Various Supervised Classifiers

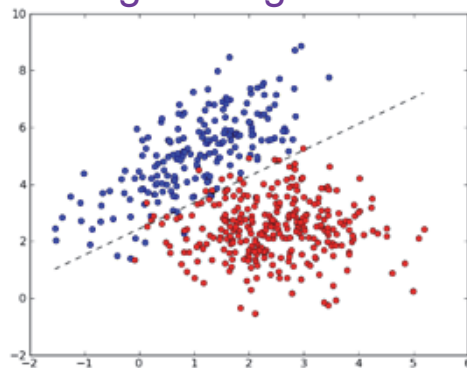
CART
(classification tree)



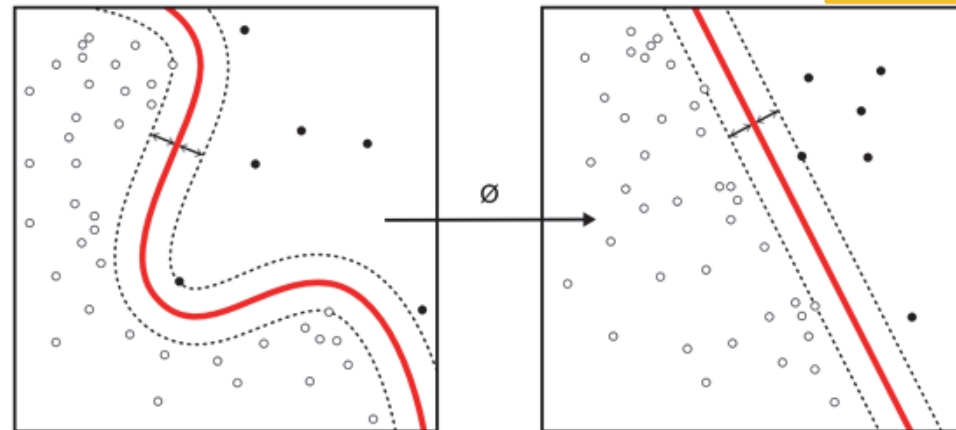
Transparency Level = high

Transparency Level = high

Logistic regression



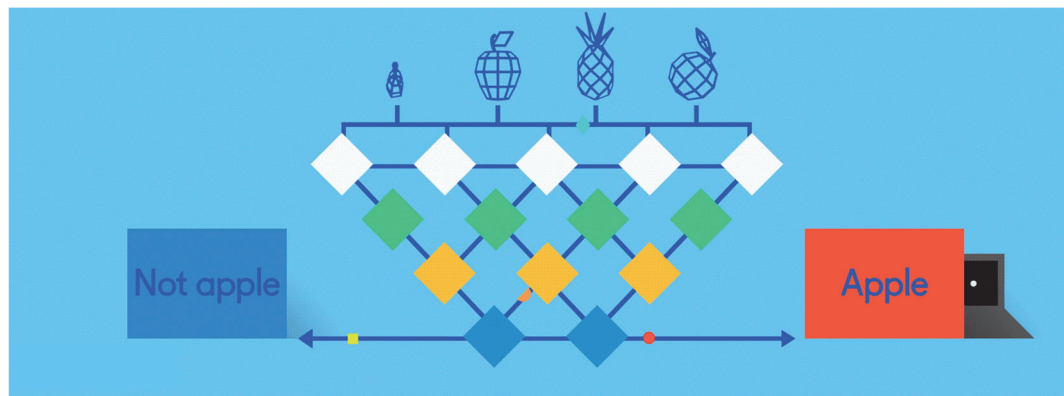
SVM



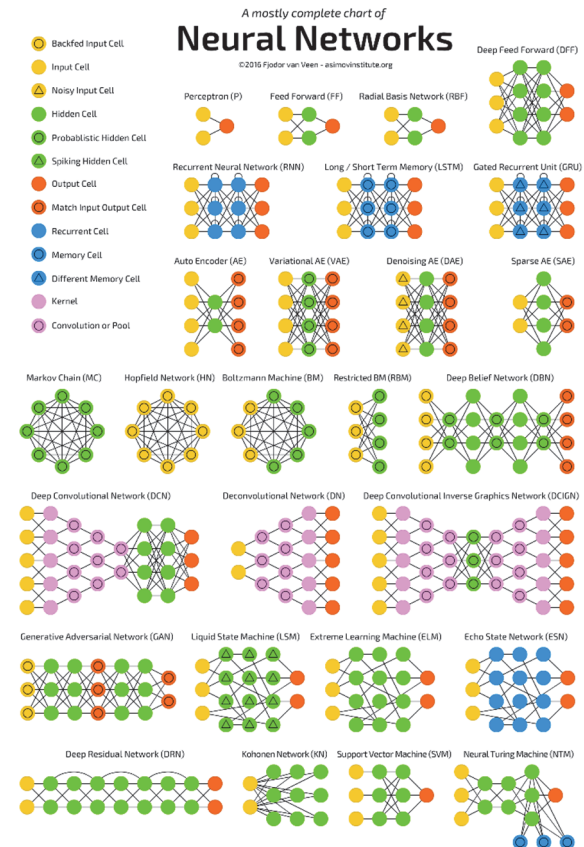
Transparency Level = mid

Various Supervised Classifiers: Neural Network

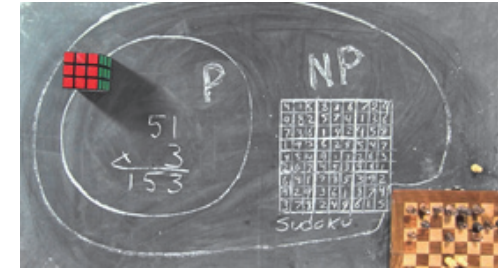
Transparency Level = (very) low



- We know X's (inputs) and Y's (outputs)
- We don't know what's going on in the hidden layers
- We have to determine the architecture of the network
→ many possible configurations



Nature of Algorithms



- Algorithm? Well... actually, most of them are heuristics
 - ✓ Forget optimization. Try to develop better heuristic.
 - ✓ Algorithm (heuristic) as strategic asset to company
 - ✓ Algorithmic competitions (competitions among intelligent agents) may end up with unstable equilibria → implication to MFN policy
- Algorithms are extremely single-minded
 - ✓ may lead to myopic decisions: business decisions using algorithms may cause tension between short-term success and long-term goals
 - ✓ may result in unintended outcomes
 - ✓ Algorithm with soft goals (or concerns)?

Algorithms still have many blind spots

AI needs some emotional intelligence?

AMERICA
Facebook Plans To Add 3,000
Workers To Monitor, Remove
Violent Content

May 3, 2017 · 12:03 PM ET

COLIN DWYER



Symbiotic relationship between human and AI

*The companies employing robo-advisors
also employ hundreds of people*

WHY ROBO ADVISOR IS BETTER FOR YOUR MONEY?



People make decisions about where to put money based on their life goals, risk tolerance, past experiences, fears, and changes in circumstances

Nature of Algorithms (continued)



- Opaqueness
 - ✓ Algorithms are black boxes (Luca et al., 2016)
 - ✓ An algorithm can tell you which employees or products or portfolios are most likely to succeed without identifying which attributes are most important for that success
- Context-(& data-) dependency of ML
 - ✓ Success in Chicago may not guarantee success in Orlando
 - ✓ Usual wisdom in data science: While increasing table length (records) will improve predictions, the real power of big data comes from table width (attributes) → Context-dep. may vitiate this wisdom



[in sum] The Nature of Algorithms

- Types of algorithms: All algorithms are not equal
 - ✓ Decision support by solution-finding (optimization-oriented) vs. Pattern recognition (classification-oriented)
- Algorithms in data science are primarily for correlation; not for uncovering cause-effect relationship
 - ✓ Correlation doesn't mean causation – “This is a prediction, not advice (Varian, 2016).”
 - eg) Short tweets will get retweeted more often than longer ones → not a suggestion that you should shorten the tweets
- single-mindedness, opaqueness, context-dependency, ... are all natural outcomes of the development path of algorithms

Legal Perspectives on Alg: Transparency

- Transparency as means of facilitating oversight and scrutiny
- F. Pasquale – Black Box Society; Pasquale (2010); Perel & Elkin-Koren (2015, 2016); Chen et al. (2011); Urban et al. (2017)
 - ✓ Google's search engine and ISPs' network management “should be transparent to some entity capable of detecting” the potential misdeeds or harms these services may create (Pasquale).
- Concealed behind a veil of a code?
 - ✓ algorithm as strategic asset to company – innovation to be protected
 - ✓ furthermore, technically impenetrable due to complexity and learning capabilities (esp. learning as a procedure for constructing a recipe)

Legal Perspectives on Alg: Accountability

- Transparency \neq Accountability – transparency alone cannot guarantee responsibility or accountability, since algorithms (due to their inherent traits) lack critical reflection
- Perel & Elkin-Koren (2015, 2016)
 - ✓ In voluntary transparency (eg, algorithmic enforcement in private sectors), the data disclosed may be partial, biased or even misleading
 - What transparency? – variable selection issue
 - ✓ Transparency may produce immense volumes of unintelligible data
 - eg) Copyright enforcement generates a huge amount of data

Accountability without Transparency?

- Alternative suggested: Black Box Tinkering (Perel & Elkin-Koren)
 - ✓ Freedom-to-tinker may facilitate social activism, creating a policy lever for checks and balances of the hidden practices of algorithms
 - ✓ Black box tinkering can allow us to check whether platforms consider fair use before automatically targeting questionable content
 - ✓ Case: (online) copyright enforcement – intermediary safe harbor regime under the DMCA (Digital Millennium Copyright Act)



Responsibility
(책임, 책무)

Accountability
(소명의 책임?)

Legal Perspectives on Alg: Suggestion

- Manageability (or controllability or responsible manageability)
 - ✓ esp. for algorithmic risk evaluation and crisis management
- With a core objective and a set of concerns (soft goals), algorithm designers and implementers could build trade-offs into their algorithms
 - ✓ constraints, multiple objectives, weights by importance, etc.
- Even in cases where transparency is not a must (eg. private use – Uber’s matching algorithm or Google’s search engine), manageability(-proof) is necessary for contingency

Legal Perspectives on Alg: Purpose

in Public Concerns

- Run afoul of justice and due process requirement?
- Bureaucratic justice, legitimacy, dignity ← issue of what reasons are behind decisions
- Verifying that it is accurate in implementing its goals and works as desired
 - ✓ But, not a piece of cake – e.g.) S/W updates in self-driving cars

in Private Concerns

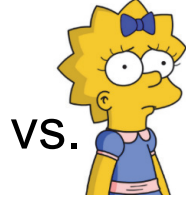
- Fair use, no illegal discrimination (Sweeney, 2013; Datta, 2015 – race or sex discrimination in search ads; but whom to blame?)
 - ✓ price discrimination? (Desai & Kroll)
- Inscrutable & hardly interpretable – remind) nature of ML (Singh et al.)
- Risk of abuse: eg) pollution attack
- Personalization issues

Discussions

- The nature of algorithm—opaqueness , context-dependency, etc.—naturally raises legal issues; but opaqueness does not mean that the algorithm governance is impossible
- Discussions on the algorithm governance have been held around transparency and accountability – but, ...
 - ✓ Transparency: “... Illusion of clarity in cases where clarity is not possible (Desai & Kroll, 2017)”
 - ✓ Transparency \neq Accountability: handing over code will not resolve the accountability issues
 - ✓ alternative: Accountability without transparency – black box tinkering

Too Much Expectation about Algorithms?

- “AI systems (thus algorithms) are not infallible”



- “They must show consistency, explain their decisions, and counter biases, or they will lose their value (Rao, 2017).” → ! or ?
- Innovation vs. Compartmentalized lawmaking
 - ✓ Innovation precludes compartmentalized lawmaking; and vice versa

- Why we require transparency and accountability?– to secure effective debugging → trust issue
- legal measures for debugging-proof mechanism + risk evaluation and crisis management function = so-called ‘manageability’
 - ✓ Develop algorithm governance on the basis of the notion of manageability
 - ✓ Provide safe harbor to (esp.) private platforms proving manageability

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