Computational constraints on algorithmic governance

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- ethical impossibility theorems

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- solutions drawn from technical literature and existing systems, such as legal

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- $\odot \implies$ regulatory architects and policymakers must consider these limitations when framing and implementing ethical AI regulation

Question: What does it mean for an algorithm or AI to be 'ethical'?Ethical computation: the algorithmic computation consists of:

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- Auditing: an algorithm is ethical if it only if it is provably (or perhaps probably) ethical i.e. if ethical status of its procedures/outputs can be audited

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- Ethical AI will be algorithmic: complex nature of algorithmic systems, large datasets and ubiquity of AI will necessitate that, by and large, *auditing/procedural* regulation of algorithms will need to be via computational means e.g. algorithms regulating algorithms

Computability

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 - (ii) is the ethical computation *efficiently* (and feasible, given resource constraints) computable?

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 - (iii) *uncertainty/risk thresholds*: if probabilistic, how are decisions around acceptable risk of unethical outcomes determined?

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- **Complexity zoo**: most problems in the universe are in fact not tractable the size of higher complexity classes vastly outstrips that of *P* and *NP* for example

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- **Maximal consistency**: must classifications by ethical algorithms form maximally consistent set?
- **Inconvenient truths**: what happens if algorithmic approaches reveal inherent contradictions within ethical norms? Should such inconvenient truths be censored? Are there algorithmic results that dare not speak their name?

- Controllability: is an algorithm ethically controllable?
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- (iii) Open (offline) v closed loop (online) control how/when should input external to algorithm be mandated:
 - open loop control humans 'in the loop' (but what are trade-offs e.g. drop in efficiency/accuracy?)
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- (iv) *Noise* how to control system subject to 'noise' (errors/uncertainty in data) e.g. fairness under measurement error [Liu et al. 2019]

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 - (iii) probabilistic ethics: use of heuristics/non-deterministic solutions can render ethical computational claims uncertain/probabilistic [Kearns et al. 2017]

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 - (i) *probably approximately ethical*: algorithmic learning of ethical labels approximate acceptable error rates?
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 Inherent Trade-Offs in the Fair Determination of Risk Scores)
 - (iii) deciding if appropriate heuristic (computationally) ethical problematic in own right
- **BUT** such challenges are ubiquitous Four C's not in principle barriers to ethical AI

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- **Controllability**: can this be controlled for in 'black box' scenario? That is, *how controllable* is the algorithm? Trade-offs between fairness of deep learning model versus how controllable

Conclusions

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- **Risk assessment of uncertainty important**: important to assess types of uncertainty and risk appetite given probabilistic or heuristic-basis for ethical classifications [Bogosian, K 2017]
- **Solutions**: learn from existing systems, such as legal systems, how consistency/complexity challenges are handled