Artificial Intelligence
Advanced Topics in AI & ML
Interpretability, Explainability, and AI Ethics

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1. Interpretability
2. Explainability

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3. Bias and Fairness in AI

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4. AI Ethics
5. AI Regulations

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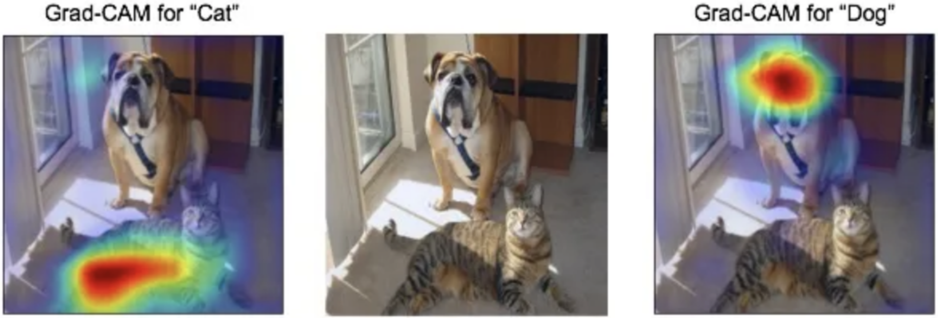

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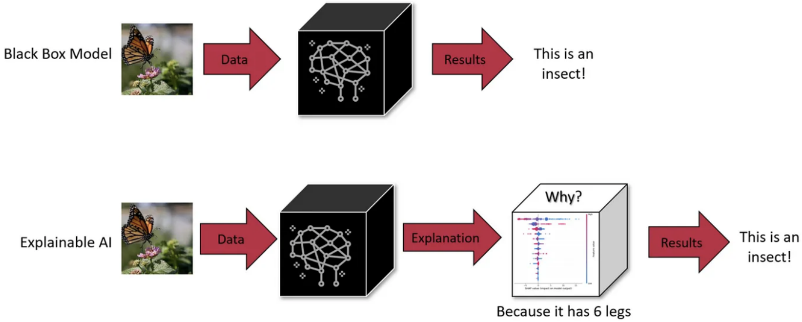

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AI Ethics

Inequity and fairness

ML can contribute to and amplify social inequity

For foundation models, it is useful to separate:

- intrinsic biases (properties in the foundation model)
- extrinsic harms (harms in specific applications)

Source tracing to understand ethical/legal responsibility

Mitigations: proactive interventions/reactive recourse

Environment

Foundation models involve significant training/emissions

One perspective: amortised cost over re-use

Several factors would be beneficial to consider:

- compute-efficient models, hardware, energy grids
- environmental cost as a factor for evaluation
- greater documentation and measurement

Economics

Foundation models may have economic impact due to:

- novel capabilities
- potential applications in wide array of industries

Initial analyses have been conducted to understand implications for productivity, wage inequality, concentration of ownership

Misuse

Misuse: the use of foundation models as technically intended but for societal harm (e.g. disinformation)

Foundation models may make misuse easier by generating high-quality personalised content

Disinformation actors can target demographic groups

Foundation models may also help to detect misuse

Legality

How law bears on development/deployment is unclear

Legal/regulatory frameworks will be needed

In the US setting, important issues include:

- liability for model predictions
- protections from model behaviour

Legal standards must advance for intermediate models

Ethics of scale

Widespread adoption of foundation models poses ethical, political and social concerns

Ethical issues related to scale:

- homogenisation
- concentration of power

How can norms and release strategies address these?

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  - Requires AI models respect democracy and human rights

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3. Interpretability deals mostly on a lower level, input/output dependencies
4. Explainability steps in on a higher level to provide a human-like explanations
5. Usually the most interpretable are simpler models; explainability can be applied to a model of any complexity

Thank you *all*!