Tri-dimensional sustainability of artificial neural networks

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Outline

Context

Social:

- Bias and inaccuracy
- Bias-variance trade-off

Environmental:

- Impact mapping
- Water consumption
- Carbon Emissions
- Raw Material Consumption
- Tertiary Effects

Economic:

- Prediction
- Information asymmetry
- Inequality

Conclusion

Context

Aims:
High-level summation of sustainability impacts of ANN.

Terminology
Artificial Neural Networks (ANN)
    Umbrella term in literature: AI.
    Derived of machine learning/deep learning.

ANN
Computer system based on the human brain

Social

Bias and inaccuracy

Uses:
Data analysis, user guidance, broaden decision-making, image recognition,

Issues:
Biases in training data lead to biases in ANN
Less effective in contexts underrepresented in their training data
No universal approach in mitigating bias and inaccuracy
Statistical analysis (which has limitations) required in ANN software
Effectiveness hampered by lack of human knowledge
Inducive bias increases training efficiency
Lack transparency
Potential to impact people's lives
Performance increase in image recognition has plateaued recently

Bias-variance trade-off

Model complexity inversely proportional to variance
Eventually leads to more error

Differing views on BVT:

Can be addressed with large, varied datasets
Trade off only partially true – variance has a weighted distribution in respect to complexity.

Environmental

Impact mapping

One study managed to map environmental impact via ANN models.

Caveats:

ANN must be optimised for specific purpose

Water consumption

Water needed to generate electricity or cool servers
Water consumption of AI models overlooked or supressed

Will increase as models get more sophisticated

Remedies for reducing carbon emissions and water consumption are mutually exclusive.
One requires access to sunlight, the other requires avoiding it.

Carbon Emissions

Can be used to track emission profiles
Algorithm can develop in unintended ways

Proportionality framework: does the task an AI is used for justify it’s carbon footprint?

As ANN and hardware get more powerful, they will use more energy.

Raw Material Consumption

ANN have the potential to reduce resource consumption in the automobile industry

ANN can be trained to adapt to hardware over it’s lifetime preventing obsolesce.

ANN have hardware requirements and resource consumption across their lifecycle.

Can reduce the number of physical experiments needed

Issues:
Expensive and exclusive to those who can afford it.
Practical restrictions reduce potential for widespread usage.

Tertiary Effects

Short term gains in using AI will have unintended consequences:

Increase in energy efficiency - Increased energy use

Automated vehicles - Increase vehicle use

Increased demand for AI - Increased demand for raw materials

Mutually Exclusive Demands:

ANN require a lot of energy and water to function - This is energy and water that could be used elsewhere.

Economic

Prediction

ANN has uses in:
Cost estimation
Predicting bankruptcy
Financial distress
Stock forecasting

Caveats :
Cost estimation: only with similar projects
Studies only focuses on specific company types
Time frame for many studies is limited
Statistical differences between industries require ANN to be tailored.

Long term analysis revealed that share return prediction was variable, episodic and unstable

Information asymmetry

Information asymmetry:
Sellers have more information than buyers and use this to their advantage.
Buyers deterred from paying higher prices
Less high-quality goods available
Market suffers

Financial reports can be manipulated; stakeholders unaware of true companies' financials.

ANN across multiple studies has shown success in financial distress prediction, credit risk detecting fraud and investigating financial sustainability impact.

ANN alone is insufficient to increase economic sustainability
Lack transparency in their decision-making process.

Inequality

Cloud connections to more powerful devices needed to use ANN.
Security and implementation complications

Implications:
Consumer-grade hardware cannot natively support ANN
Compound economic inequalities with inequality in ANN implementation

Conclusion

ANNs have the potential to help with the collation and analysis of data, decision-making and forecasting.

Bias and inaccuracy can be borne of training data and human/statistical limitations.

They require energy and water to operate, and the mitigation strategies for both are mutually exclusive.

Unintended consequences may arise, including increased resource consumption and said resources being expended as opposed to others in more dire need.

Regarding finance, ANNs are not practical for long-term forecasting of share returns, though they can be effective in very specific conditions provided the ANN is tailored to the industry.

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