AI: Strategy + Marketing (MGT 853)

Course Wrap (Session 11-13)

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Yale School of Management

Spring 2025

ML Failures

- The Hidden Autopilot Data That Reveals Why Teslas Crash – WSJ

Course Overview

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- Module D: Project Presentations + Guest speaker (AI / ML in a real business) + Course Wrap

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- ML typically relies on human-generated data to succeed

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- How Deep Learning architecture can vary (image / sequence data)
- Generative models use self-supervised learning
    - Have prediction at their core (e.g. LLMs with next-work prediction)

4. AI Decision-Making Framework

- AI Decision Making Framework: Input, Prediction, Judgment / Decision, Action, Feedback

Prediction and Decision

Understand the difference between prediction and decision (not always clear)
Prediction should be an input into your decision, not the other way around.

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  - What if you cannot get full coverage of y variables?

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- New explainability approaches like GRAD-CAM can help highlight important areas

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- *Confusion matrix* – Do not rely on accuracy as being sufficient. False Negatives NOT the same as False Positives.

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- Use Proxy variables and semi-supervised learning for match happiness

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- Salesforce can lose because of AI (commission on sales of \$30K $\Longrightarrow$ \$7K)
- Need to *redesign the business model* after AI is introduced

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- Products are bundles of characteristics. Expensive Black blouse = Style + Material + Color + Price etc. Can learn at the level of characteristics, rather than products.
- Store Managers and AI: Managers can really help AI work better, but have no incentive to help. Need to (re)design incentive structure.

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- Fairness and Bias can potentially arise at any stage of the ML pipeline
- Do you want to incorporate fairness considerations in ML? Ethical and Legal considerations
- Many definitions of fairness – which one is right for your project?
- Research shows you cannot achieve all ideas of fairness – mutually contradictory

11-13: Projects – take us beyond the lectures to many different, unexplored areas of AI / ML.

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- Focus in course on concepts that are unlikely to change.

Can AI teach us about the past?

AI in Society

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- Not just the present but also the past $\Longrightarrow$ Ancient Herculaneum in present day Italy

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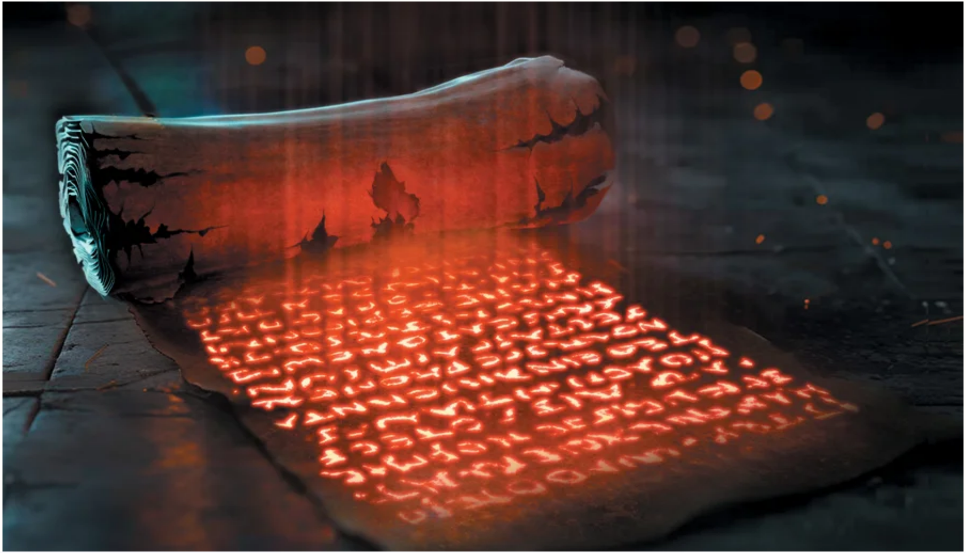

Speaking of the Future...

Course Evaluations

Course Evals

- Now it is time for you to evaluate!
- Please provide detailed feedback at:
- https://students.yale.edu/oce-submissions/