9.1: Intro to Causal AI

Instructor: Dr. GP Saggese - gsaggese@umd.edu

References:

- Easy:
  - Hurwitz, Thompson: Causal Artificial Intelligence: The Next Step in Effective Business AI, 2024
- Medium / Difficult
  - AIMA
  - Facuce

- ***Causal AI***
  - Why Causal AI?
  - The Ladder of Causation
  - Correlation vs Causation Models

- Causal AI
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Big Data and Traditional AI

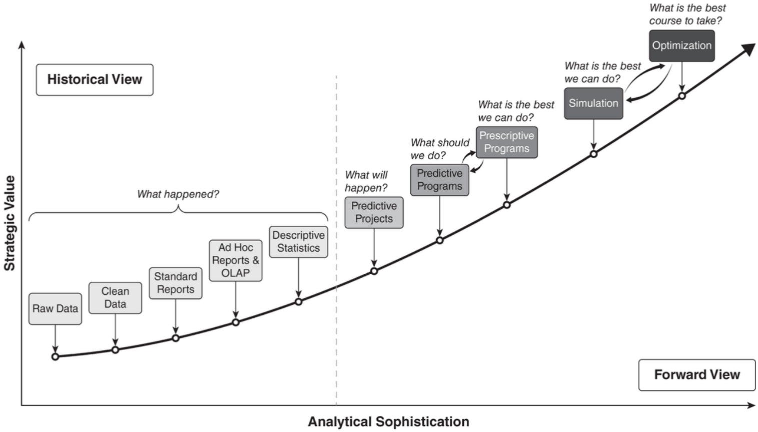
- For the past 10 years, **focus of analytics** on:
  - Organize and analyze massive amount of data
  - Data analytics (dashboards, models, reports)
  - Run machine learning on data
- Problems with **traditional AI**
  - Predicts based on observed correlations
  - Can't explain why an outcome occurred
- **AI in decision making**
  - Understand impact of decisions
  - E.g., *"What happens if a product price is reduced by 10%?"*
    - Will more customers buy?
    - If revenue decreases, what to do?
    - Why are customers leaving? Quality issue? Emerging competitor?

What Are Data Analytics?

- **Collections of data**
  - Aggregated, organized data sets for analysis
  - E.g., customer purchase histories in a CRM system
- **Dashboards**
  - Visual displays of key metrics for insights
  - E.g., dashboard showing quarterly revenue, expenses
- **Descriptive statistics**
  - Summary metrics: mean, median, mode, standard deviation
  - E.g., average sales per quarter to understand trends
- **Historical reports**
  - Examination of past performance
  - E.g., monthly sales reports for past fiscal year
- **Models**
  - Statistical representations to forecast, explain phenomena
  - E.g., predictive model to anticipate customer churn based on behavioral data

Data Analytics Sophistication

Business Question	Methodology
What happened?	Descriptive statistics
What will happen?	Predictive models
What should we do?	Prescriptive programs
What's the best we can do?	Simulation + optimization



Explainability

- **Regulators** require that if you are making decisions using ML / AI, you should be able to defend the results of your analysis
  - E.g., decide who to hire, how to set up a policy
- Organizations can:
  - Be **fined** by regulatory authorities
  - Face **backlash** from customers and activists
- E.g., neural networks are "black boxes"
  - Lack of explainability
    - Humans can't understand how inputs are combined into a conclusion
    - Cannot explain to shareholders why certain decisions were made
  - Bias
    - E.g., using age, race, sex as a feature can introduce bias
- **Explainable AI** allow users to:
  - Comprehend
  - Explain
  - Trust the results by the machine

Correlation is Not Causation!

- Correlation is a statistical method for understanding relationships between data
  - Pros
    - Use past outcomes to predict future outcomes by finding patterns and anomalies
  - Cons
    - Doesn't explain the cause
    - Variables may move together due to coincidence or a hidden factor
- Causation explains how changing one variable influences the other
  - Cannot be concluded from correlation alone
- **Data does not understand causes and effects**
  - Only humans can identify variables and relationships based on context
  - Without causation, you can't make intelligent decisions

Causal AI

- **Understands the why**
  - Determines cause-and-effect between variables
  - E.g., whether a marketing campaign increased sales
- **Identify interventions**
  - Identifies variables and interventions to change outcomes
  - E.g., which lifestyle changes reduce blood pressure
- **Predicting counterfactuals**
  - Hypothesizes outcomes under different circumstances
  - E.g., student grades if they attended a different school
- **Avoiding bias**
  - Traditional AI biased by training data and ignored variables
  - Ensure fairness by accounting for confounding variables
- **Improving decision-making**
  - Provides understanding of relationships for better decisions
  - E.g., improving supply chain by understanding logistic impact

Causal AI vs Traditional AI

- *"The next revolution of data science is the science of interpreting reality, not of summarizing data"* (Judea Pearl, 2021)
- Current AI uses correlation to:
  - Analyze data
  - Identify patterns
  - Make predictions
- Models depend on data quality
  - Biased or unclean data $\implies$ poor model

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The Ladder of Causation

- Pearl provided a 3-layer framework for understanding causality

Level	Symbol	Activity	Typical Questions
1. Association	$\Pr(Y \vert X)$	Observing	What is?
2. Intervention	$\Pr(Y \vert do(X), Z)$	Intervening	What if?
3. Counterfactuals	$\Pr(Y_X \vert x', y')$	Imagining	Why?

Rung 1: Association

- **Question**: *"How would seeing X change our belief in Y?"*
- **Symbol**: $\Pr(Y|X)$
  - Bayesian update
- **Activity**
  - It is just "passive observation"
  - Determine if two things are related
  - Traditional AI and ML is based on this
- **Example**
  - *"The tree has green leaves during spring"*
  - *"What does a symptom tell you about a disease?"*
  - *"What does a survey tell you about the election results?"*

Rung 2: Intervention

- **Question**: *"What happens to Y if you do X?"*
- **Symbol**: $\Pr(Y|do(X), Z)$
- **Activity**
  - Understand the impact of an action
  - E.g., *"tree has green leaves"* vs *"spring makes tree leaves turn green"*
  - Association is just about observations
  - Interventions involve "doing something" and need a causal model
- **Example**
  - *"Why did the headache go away?"*
    - "Because the pain reliever" or "Because you ate food after skipping lunch"
  - *"If you take aspirin, will your headache be cured?"*
  - *"What if you ban sodas?"*

Rung 3: Counterfactuals

- **Question**: *"Was X that caused Y?"*
- **Symbol**: $\Pr(Y_X | x', y')$
- **Activity**:
  - Imagine what will happen if facts were different
  - Predicting an outcome is the highest form of reasoning
    - It requires to understand relationships between cause and effect
- **Example**
  - Scientific experiments: *"What if we give a child an adult dose of a drug?"*
  - Litigation: *"What would the jury conclude?"*
  - Marketing: *"Why did my marketing campaign fail to generate sales?"*

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Correlation vs Causation Model

- **Correlation** = identify how variables are related to each other
- **Causality** = determine whether one variable causes another variable
  - Both:
    - Accept inputs and transform them to compute predictions
    - Identify how variables are related to each other
  - Correlation-based AI works well when there is abundant historical and observational data
  - Causal-based AI first creates a business-focused model before integrating data

Correlation-Based Model Process

- **Correlation-based AI** is "data first"
  - The more data collected the better
- **Modeling process**
  - Acquire data
  - Integrate and clean data
  - Exploratory data analysis (EDA)
  - Feature engineering
  - Build and test models
  - Deploy models in production
- **Many AI projects fail because**
  - Cultural and organizational issues
  - Models are opaque and lack explainability
  - Spurious correlations
  - Missing articulating "what's the goal of doing ML?"

Causation-based Model Process

- **Causal AI** is "model first"
  - Understand business question before ingest and transform the data
- **Modeling process**
  - What is the intended outcome?
  - What is the proposed intervention?
  - What are the confounding factors?
  - What are the effecting factors?
  - Create a model graph or diagram
  - Data acquisition
  - ...