



## MSML610: Advanced Machine Learning

### 9.1: Intro to Causal AI

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#### References:

- Easy:
  - Hurwitz, Thompson: Causal Artificial Intelligence, 2024

- ***Causal AI***

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

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

# Big Data and Traditional AI

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- 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?

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- **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**

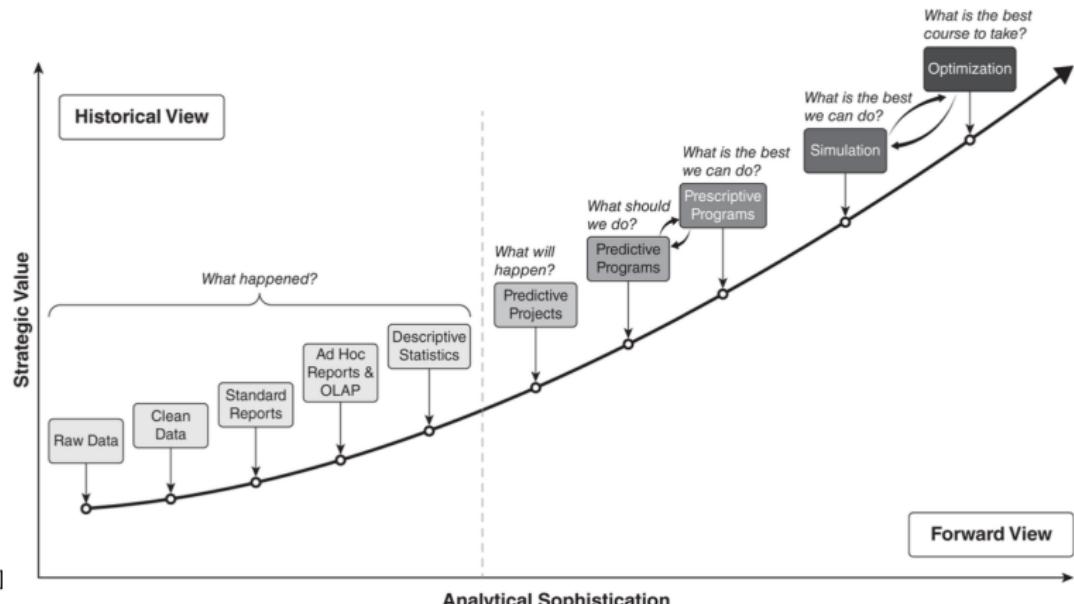
- Examination of past performance
- E.g., monthly sales reports for past fiscal year

- **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

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- **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!

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- **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

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- **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

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- “*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

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

# The Ladder of Causation

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- Pearl provided a 3-layer framework for understanding causality

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

# Rung 1: Association

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- **Question:** “*How would seeing X change our belief in Y?*”
- **Symbol:**  $\text{Pr}(Y|X)$ 
  - 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

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- **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

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- **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?*”

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

# Correlation vs Causation Model

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- **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

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- **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

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- **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
  - ...