

# Medicine to Math: Statistics, Machine Learning, and AI

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#### **Agenda**



#### Why This Talk?

- Medicine increasingly relies on mathematical models
- From bedside decisions to AI-driven care
- Goal: Understand the journey from statistics to AI



URRENT ISSUE 

✓ SPECIALTIES 

✓ TOPICS 

✓ MULTIMEDIA 

✓ LEARNING/CME 

✓ AUTHOR CENTER

#### AI in Medicine



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Artificial Intelligence has tremendous potential to advance clinical practice and the delivery of patient care.



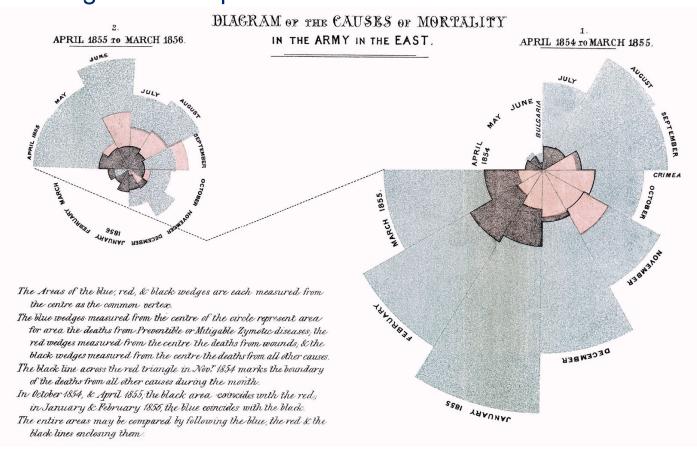


# **Statistics**



#### Florence Nightingale: Data

- Florence Nightingale: data visualization & mortality stats
- Antiseptic techniques validated statistically
- Math changed clinical practice







#### BIOMETRIKA.

#### THE PROBABLE ERROR OF A MEAN.

BY STUDENT.

Introduction.

Any experiment may be regarded as forming an individual of a "population" of experiments which might be performed under the same conditions. A series of experiments is a sample drawn from this population.

Now any series of experiments is only of value in so far as it enables us to form

### William Gosset: A Beer Story

- Developed by William Sealy Gosset at Guinness Brewery
- Used for quality control in beer production
- Compare two small samples to determine significance



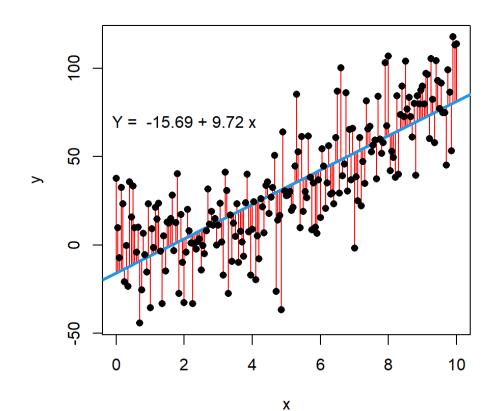
#### **From Evidence to Prediction**

- Descriptive Statistics
  - T-test used in medicine to compare treatment vs control
  - Introduced concept of statistical significance
  - P-value
- Evidence-Based Medicine (EBM):
  - Treatment A vs. Treatment B
  - Is there a real difference? (p-value, statistical significance)
- But what's next?
  - Beyond describing differences → predicting outcomes
  - Not just "Which is better?" but "How do variables interact?"
- Shift in focus:
  - From comparing two fields → mapping the landscape
  - Understanding relationships among parameters to forecast what matters most



#### The Rise of Predictive Statistics

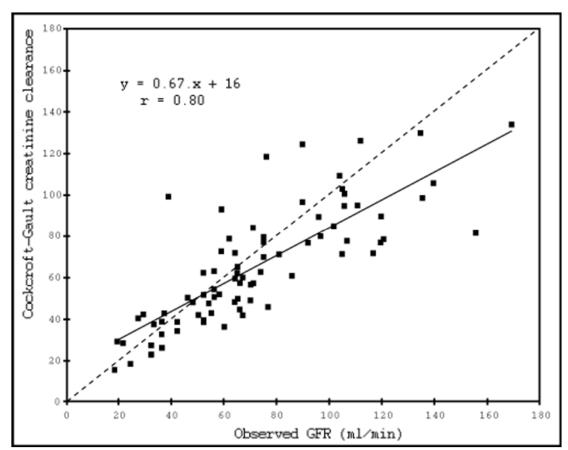
- Linear regression: fitting a line through data points
- Predictive formula: y = mx + b





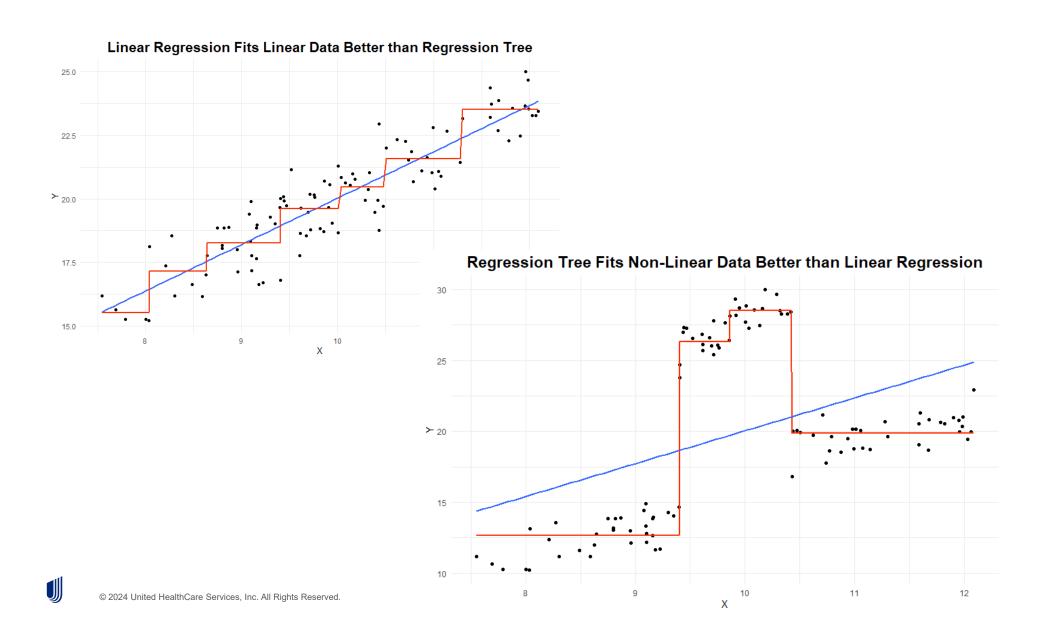
#### **Medical Example**

- Creatinine clearance (Cockcroft-Gault equation)
- Predicting GFR from age, weight, serum creatinine



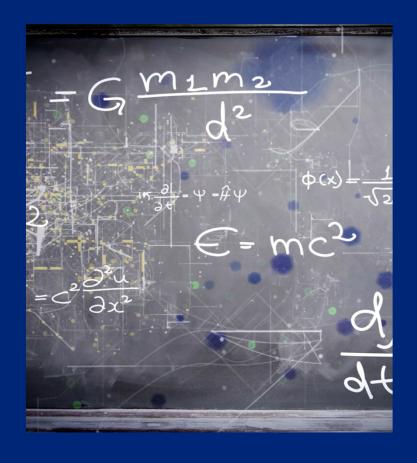


#### Real life data may not be linear





# Machine Learning





#### From Regression to Machine Learning

#### • Regression:

- Fits a single line or curve to predict outcomes
- Assumes a known functional form (e.g., linear)

#### But real-world data is complex:

- Non-linear relationships
- Multiple interacting variables

#### • Enter Machine Learning:

- Automates prediction without predefined formulas
- Uses branching decisions (trees) and iterative optimization
- Goal: Minimize error across many possible splits and models

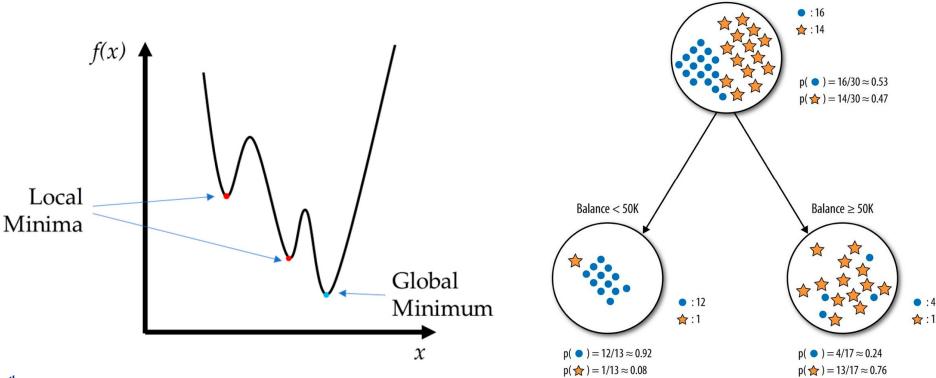
#### • Think of it as:

Regression on steroids → adaptive, multi-dimensional, data-driven



#### **Decision Trees**

- Splitting data into branches based on features
- Entropy & information gain
- Analogy to calculus finding minima

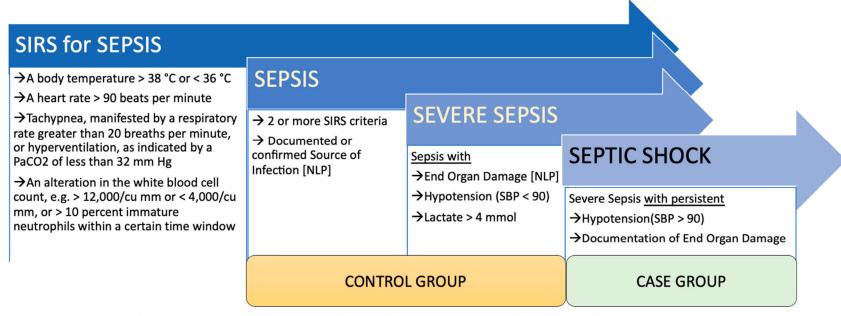


Entire population (30 instances)



#### **Medical Applications**

- Predicting readmissions, sepsis alerts, imaging classification
- Utilization management: predicting if the request is going to be an approval

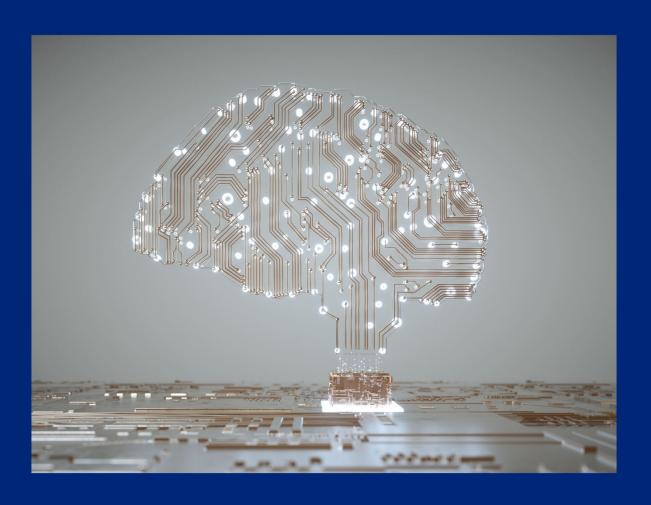


[NLP]: Data extracted using natural language processing applied to provider notes (unstructured sources)





## AI: Neural Networks



#### **From Features to Context**

#### Machine Learning:

- Uses features to make predictions
- Relationships assumed to be fixed

#### • But reality is dynamic:

Meaning depends on order, proximity, and context

#### Example:

- "Mark, a vegetarian, eats shoots and leaves"
- vs "Mark, the serial murderer, eats, shoots, and leaves"

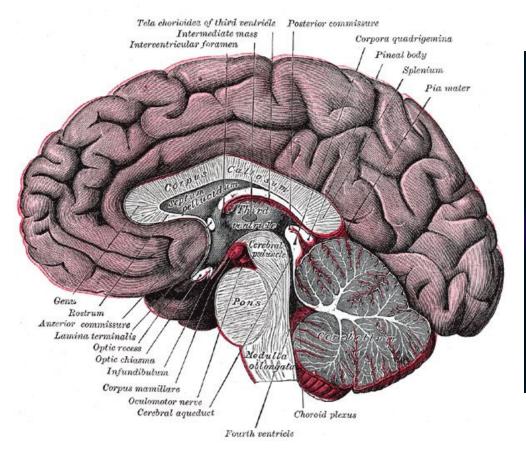
#### This is AI today:

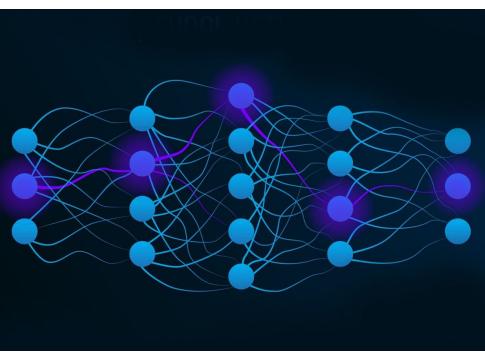
- Models that understand patterns in context, not just features
- Foundation of language models and contextual prediction



#### **Neural Networks: Inspired by the Brain**

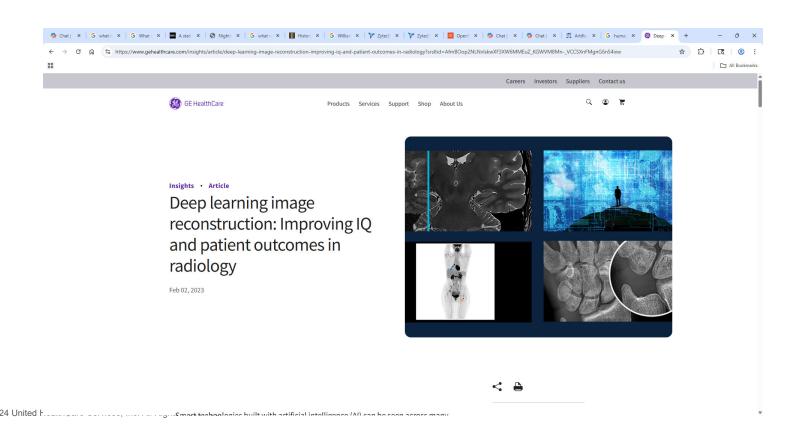
- Layers of nodes with weighted connections
- Goal: minimize cost function (error)
- Backpropagation = learning





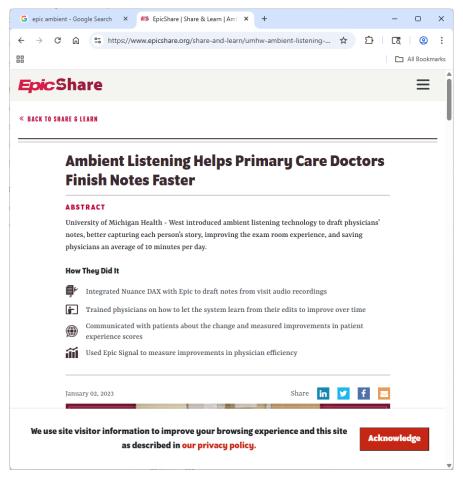
#### **Deep Learning in Medicine**

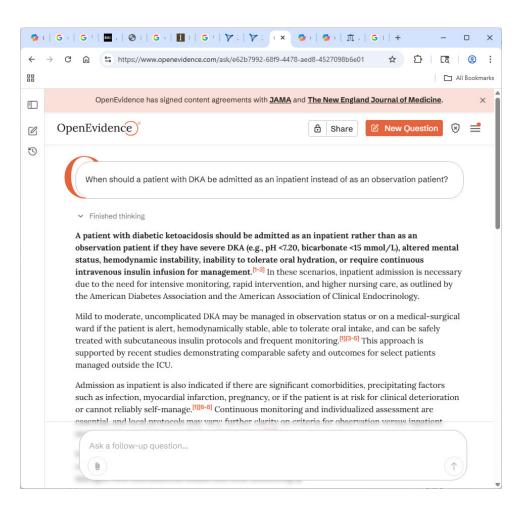
- Radiology: image interpretation
- Pathology: pattern recognition
- Predictive models for disease progression



#### Large Language Models (LLMs)

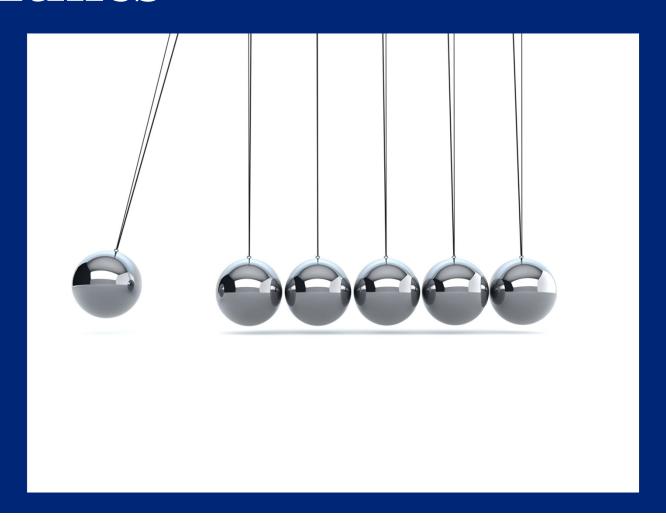
- Predicting next word using probabilities
- Trained on massive text corpora
- Emergent reasoning







# Ethics



Different ethical theories provide distinct frameworks for determining what is morally right or wrong. These theories may be drawn upon when ethical decisions need to be made in a variety of different contexts, guiding what a potential 'right' course of action should look like based on contexts such as people, community values, principles and potential consequences.

#### Deontological

- Immanuel Kant

Deontological ethics focuses on the nature of actions rather than their consequences. The philosophy emphasises the importance of individuals following their established moral rules, duties or principles, regardless of the outcomes.

#### Utilitarian

- Jeremy Bentham & John Stuart Mill

Utilitarian ethics examines the morality of actions based on their potential consequences. It focuses on maximising happiness or minimising suffering for all parties involved.

For example, If lying in a

#### Virtue

- Aristotle

A virtue is a positive trait or characteristic that is considered morally good in an individual. Virtue ethics focuses on the moral character of individuals. The theory emphasises the development of these traits and values as a means to determine the right and wrong courses of action.

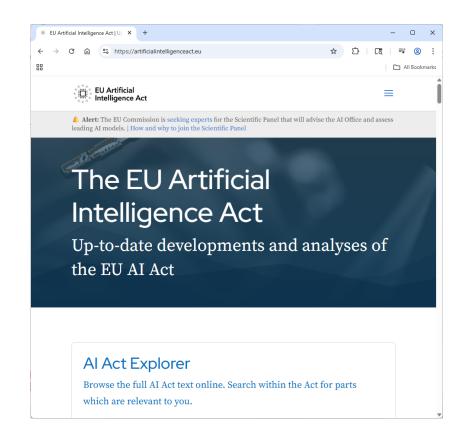
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# Ethical Foundation s: Principlism in AI

- Autonomy → Transparent AI systems with informed consent and explainability
- Beneficence → AI that enhances clinical outcomes and supports decision-making
- Non-maleficence → Rigorous testing and post-market surveillance to prevent harm
- Justice → Bias mitigation and equitable access to Aldriven healthcare

#### **EU AI Act: A Global Benchmark**

- World's first comprehensive AI legislation (2024)
- High-risk AI systems must meet strict requirements:
  - Transparency and explainability
  - Human oversight
  - Bias detection and mitigation
  - Data governance and privacy
  - Fundamental rights impact assessments
- Prohibited practices include:
  - Social scoring
  - Biometric categorization based on sensitive traits
  - Emotion recognition in sensitive contexts







# Bias Prevention & Sensitive Group Protection

- Demographics drive health outcomes
- Al can amplify existing disparities
- Medicine is heterogeneous
- Variance matters
- Unaddressed bias will lead to real-world harm





### Human Oversight & Clear Regulatory Guidance

- Al mimics human intelligence—but inherits human flaws
- Imagine medicine without human oversight
- Humans must stay in the loop
  - Auditing and review of critical decisions
  - Predefined oversight mechanisms and checkpoints
- Oversight and regulation must be designed a priori, not retrofitted





# Transparency & Explainability

- Ability to check the reasoning process builds trust
- Explainability = Trust
- Neural networks are flexible but opaque → often a "black box"
- Noise vs. Information
  - Humans must perform sanity checks to ensure noise is filtered and conclusions make sense
- Testing must be transparent
  - Processes should be repeatable, auditable, and explainable



#### Conclusion: The Dawn of a New Era

#### The Age of Al is here

- Like past revolutions: agriculture, industry, electricity, computation, internet
- You don't need to code to understand Al
  - Just as you don't need anatomy biochemistry to understand humans
- Al is your new coworker and assistant
- Our responsibility:
  - Understand its underpinnings, strengths, and weaknesses.
  - Understand the philosophy and ethics of this new creation
- Shape this tool for the good of our communities



