

# Artificial Intelligence and the Future of Pharmacy: Separating Myths from Facts

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# Relevant Financial Relationship Disclosures

- Scott Nelson has served on an advisory board for:
  - Merative Micromedex
  - Baxter Healthcare Corporation
- All relevant financial relationships have been mitigated.

# Learning Objectives



At the completion of this activity, learners will be able to:

1. Describe potential uses for artificial intelligence in pharmacy practice.
2. Compare approaches for training machine learning models.
3. Assess challenges and limitations of artificial intelligence in clinical practice.

# Predicting the future of healthcare



# ASHP Foundation Pharmacy Forecast 2024

Health systems will embrace a “**digital-first**” approach to patient encounters (e.g., video primary care visits, telehealth, and remote patient monitoring) which will make patient access to virtual care universal.



Accelerating adoption of an advanced technologies (e.g, remote patient monitoring, artificial intelligence, data integration) will **close the gap on health care disparities**.



Health system ethics committees will have expertise that ensures the **equitable application of artificial intelligence technology when used in patient care**.



■ Very Unlikely   ■ Somewhat Unlikely   ■ Somewhat Likely   ■ Very Likely

# ASHP Foundation Pharmacy Forecast 2024

Integration of electronic health record data with clinical decision support algorithms will automate drug dosing adjustments (e.g., renal, weight-based, age-based dosing)



State boards of pharmacy will develop regulations allowing the use of artificial intelligence or other technology in place of pharmacist order review and verification.



■ Very Unlikely   ■ Somewhat Unlikely   ■ Somewhat Likely   ■ Very Likely

FUTURE

OF

HEALTHCARE

DIGITAL

HEALTH



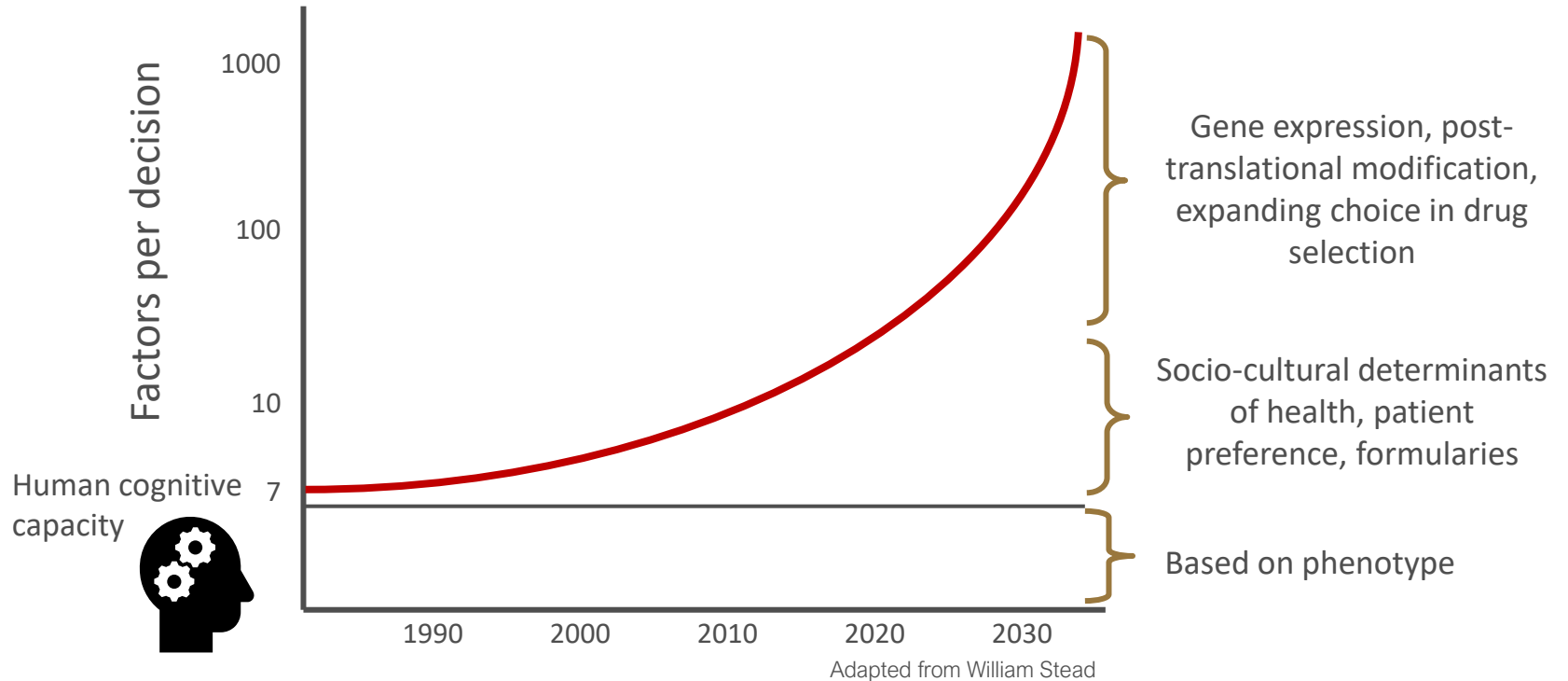
# What is “digital health”?

- An **umbrella term** for **applying** information and technology in healthcare to make a tangible difference in patient health
- Examples:
  - Wearable devices
  - Mobile health (mHealth)
  - Telehealth
  - Remote patient monitoring
  - **Application of AI**
  - Etc...

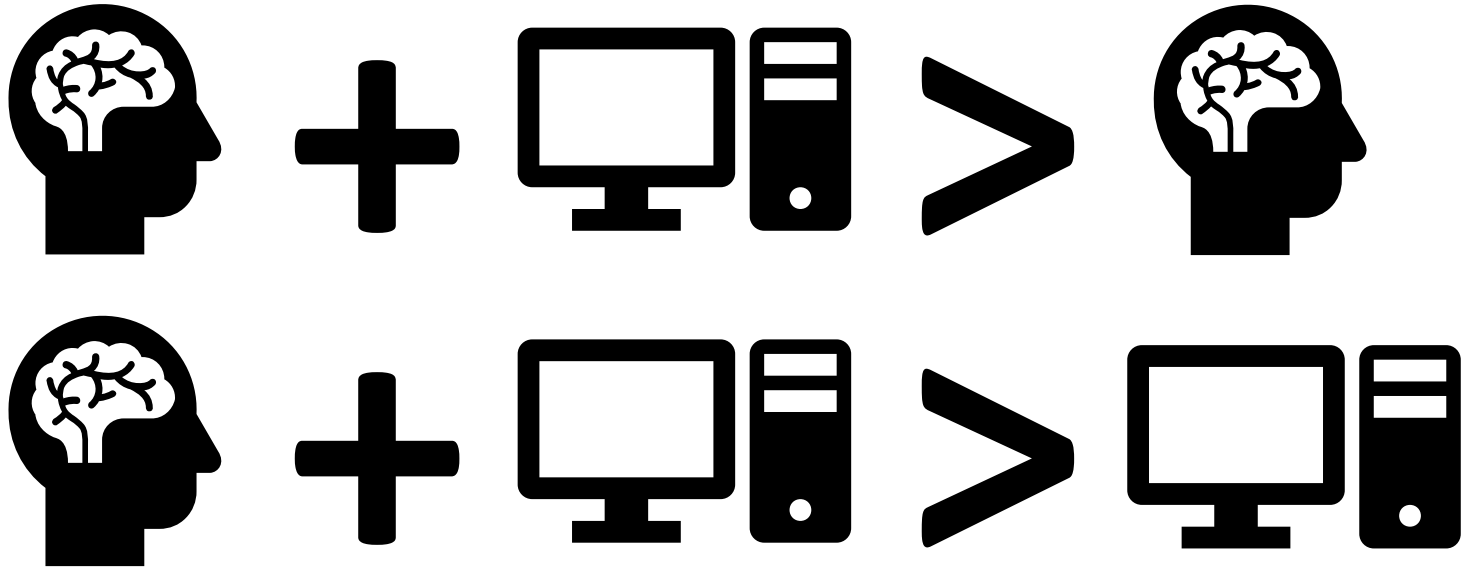




# Human cognitive capacity is $7 \pm 2$



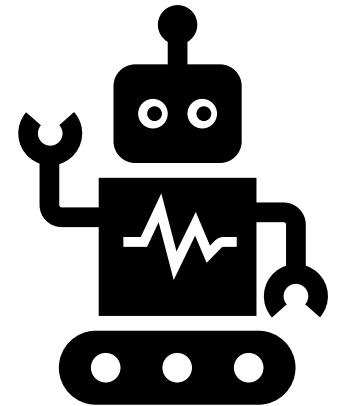
# AI = Augmented Intelligence



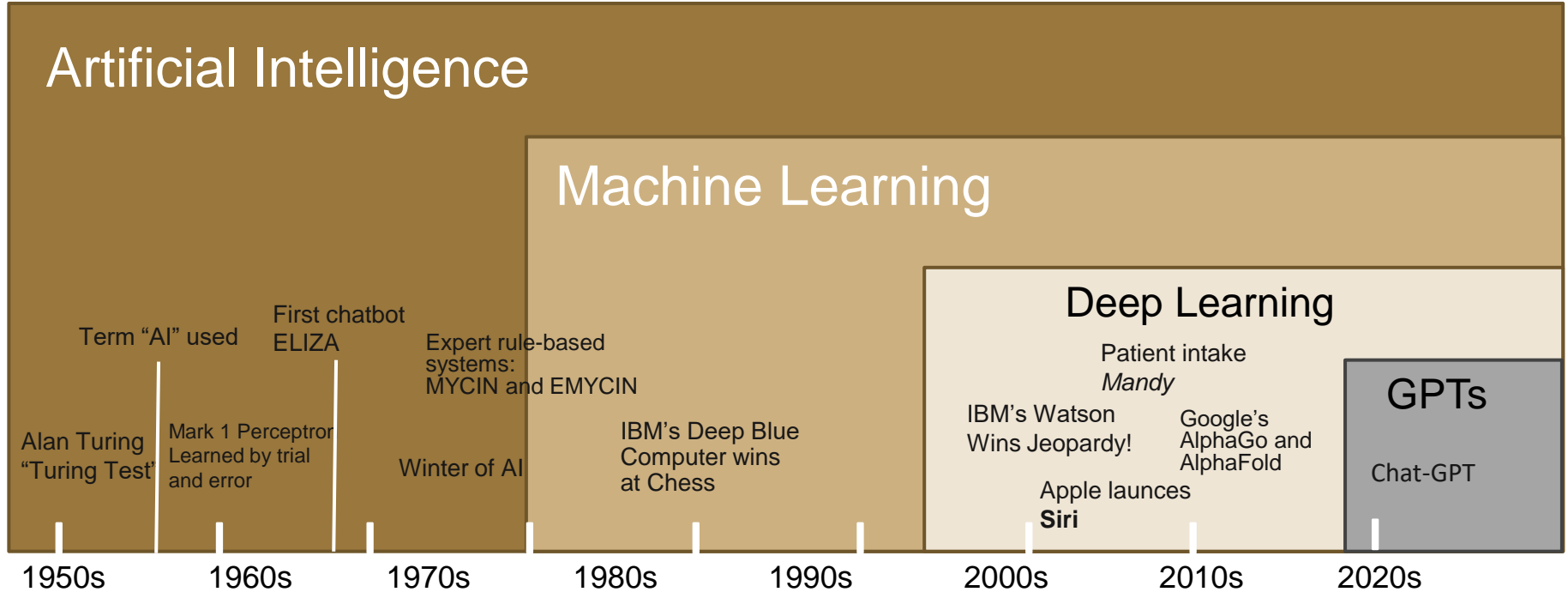
Fundamental Theorem of Informatics

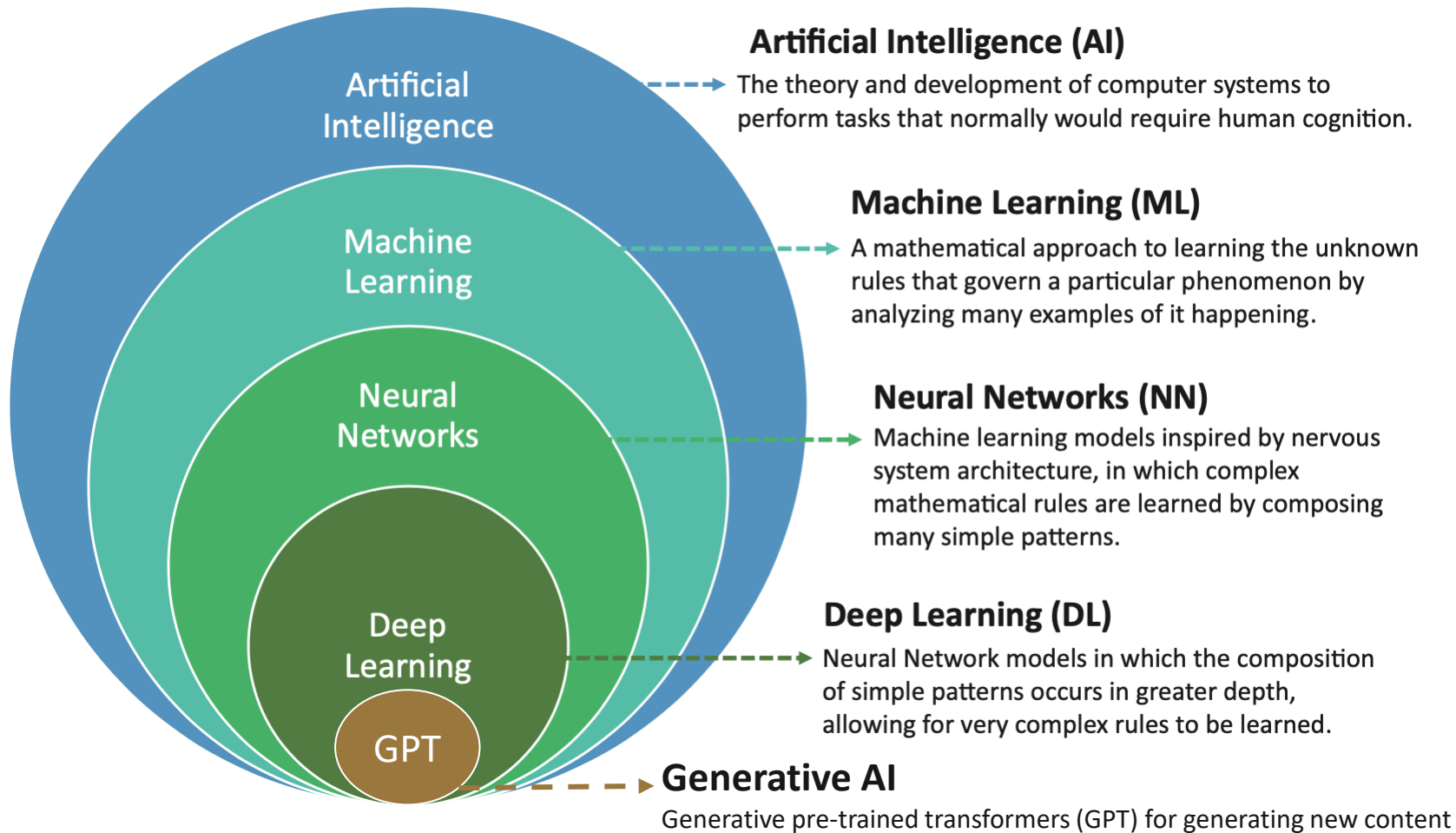
# What is AI?

- Artificial intelligence describes a computer system's ability to perform a task that would normally require human cognition.
  - Perception, language processing, learning, planning, problem solving, etc.
- General vs Narrow AI
  - General AI is still a far-off reality
  - Narrow AI
    - Can do one well-defined task, but that's it



# History





# Basic AI (expert systems)

**RX High (1)**

**NOTICE:**

You are receiving this alert because you are verifying an **angiotensin-converting enzyme inhibitor (ACE-I)** or an **angiotensin receptor neprilysin inhibitor (ARN-I)** when the patient may have received an ACE-I or ARN-I within the past **36 hours**.

Administration of an **ACE-I or ARN-I** within **36 hours** of each other is **contraindicated**.

If clinically appropriate, please hit "Cancel" and contact provider to discuss alternative therapies or re-timing of orders to allow appropriate 36 hour washout period.

**ACE-I/ARN-I Medication Orders (From admission, onward)**

Start	Ordered
03/11/21 0900	03/11/21 0728

**ACE-I/ARN-I Medication Administrations (last 36 hours)**

Date/Time	Action	Medication	Dose
03/10/21 0950	Given	lisinopril 5 mg tab(s) (ZESTRIL, PRINIVIL)	5 mg

Accept Cancel

## Medication alerts

Often lack ability to consider patient specific criteria "out of the box"

## Custom alerts

More likely to consider patient specific factors  
Example: alert for ACE-I and ARN-I overlap that accounts for administration data

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## Patient Risk/Scoring Tools

Refreshed 3 minutes ago Search Current Locat...

PTA Med Score (Adult)	PTA Medrec Score (Peds)	Admission Med Rec Complete?	Admission Med Rec Complete?	Med List Status
53				Complete
53				
43				complete
41				

Female / 45 y.o. / ...

Male / 13 y.o. / 1/...

Female / 51 y.o. / ...

Female / 52 y.o. / ...

Unit Room Bed:10

Profile PTA Meds Scoring Overview

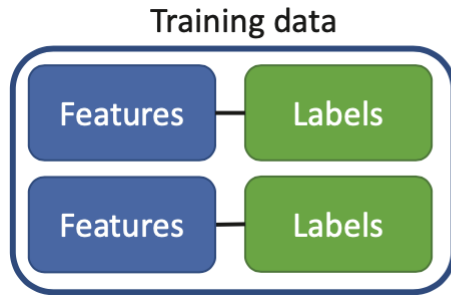
Vitals History

**53 PTA Medrec Score (Adult)**

Score calculated: ...

- 0 Age > 60 (1 pt) or > 70 (3 pts) or > 80 (5 pts)
- 3 Problem List Items
- 22 Poly-Pharmacy (10 or more meds)
- 22 High-risk PTA Meds
- 1 Inpatient status
- 0 Unknown medication ordered
- 0 CrCl < 30 in past 2 weeks
- 0 Med List NOT reviewed in past 12 months and age > 50
- 5 Admissions in the past 180 days

# Machine learning – Supervised



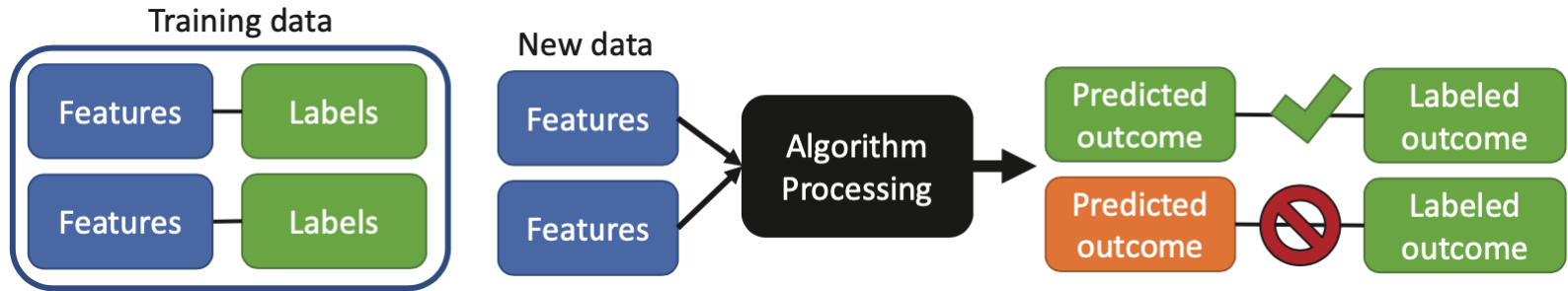
Data linked to the outcome of interest

Features = input variables

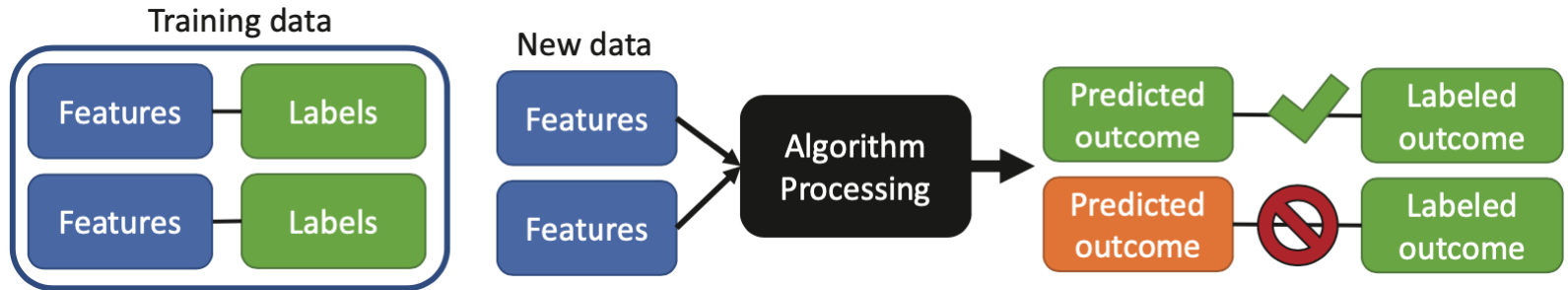
Labels = the outcome to predict



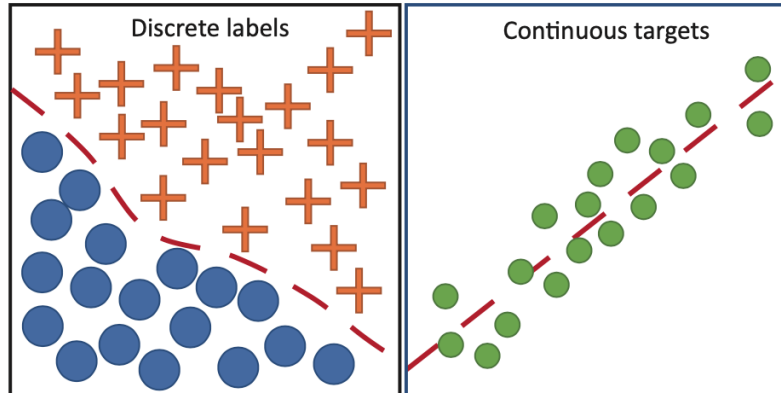
# Machine learning – Supervised



# Machine learning – Supervised



**Classification**  
Has condition or not



**Regression**  
Predicting a number value

# Examples

- **Prediction:**

- Abnormal medication orders
- Adverse drug events
- Acute kidney injury
- Readmissions
- Sepsis early detection
- Drug or glucose levels
- Etc.

- **Image processing:**

- Quality control and documentation
- Pill identification
- Highlight potential errors in verification
- Screening for disease (diabetic retinopathy, skin cancer, etc.)

# Know your labels

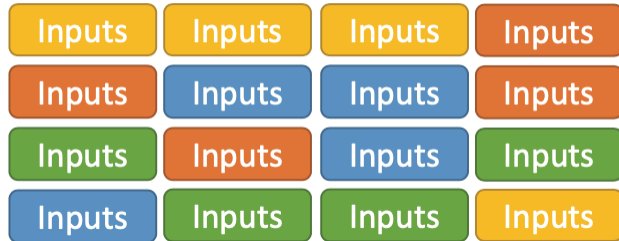
- External validation of a widely implemented proprietary sepsis prediction model in hospitalized patients
  - Wong A, Otles E, Donnelly JP et al. *JAMA Intern Med.* 2021; 181(8): 1065-70.
- Model failed to identify two-thirds of **sepsis patients**

# Know your labels

- External validation of a widely implemented proprietary sepsis prediction model in hospitalized patients
  - Wong A, Otles E, Donnelly JP et al. *JAMA Intern Med.* 2021; 181(8): 1065-70.
- Model failed to identify two-thirds of sepsis patients
- Vendor used **ICD-9 codes** for their model as the labels
  - CDC and CMS don't use billing codes for sepsis quality measures
- Also had different definitions for when a patient developed sepsis
  - Vendor used encounter-level performance, whereas the study used prediction-level performance (alerts) where the outcome = “sepsis in the next x hours”

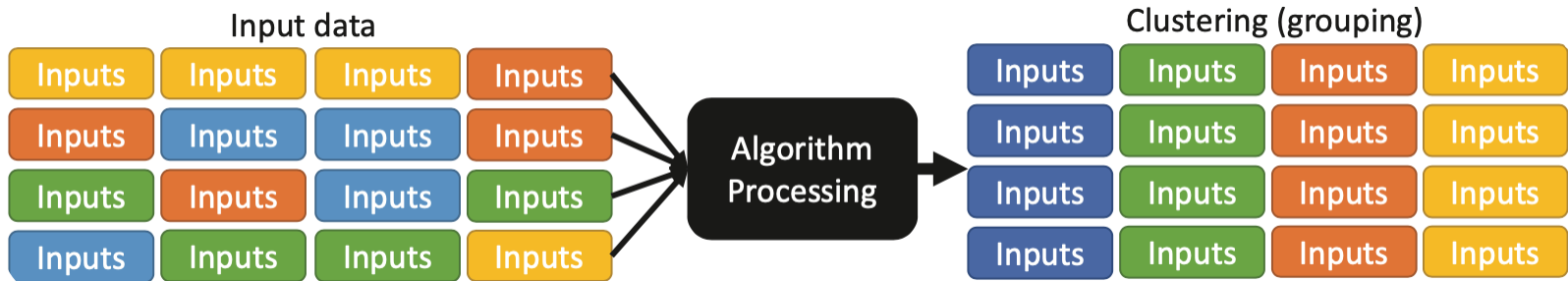
# Machine learning – Unsupervised

Input data



No labels

# Machine learning – Unsupervised



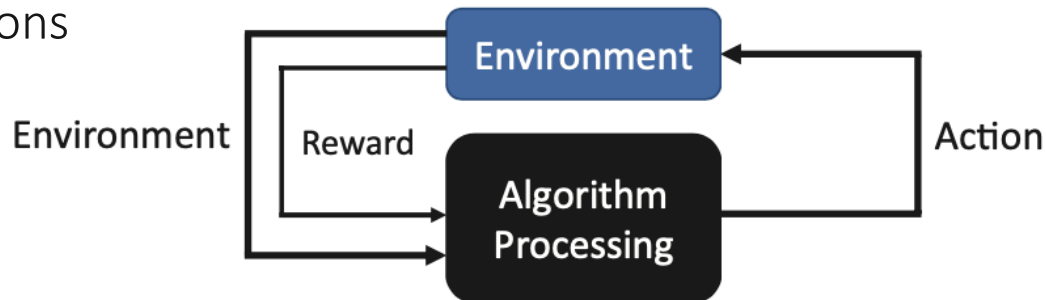


# Examples

- Data analytics
- Natural language processing
- Auditing
- Drug diversion
- Cluster analysis
- Population identification (phenotypes)

# Others

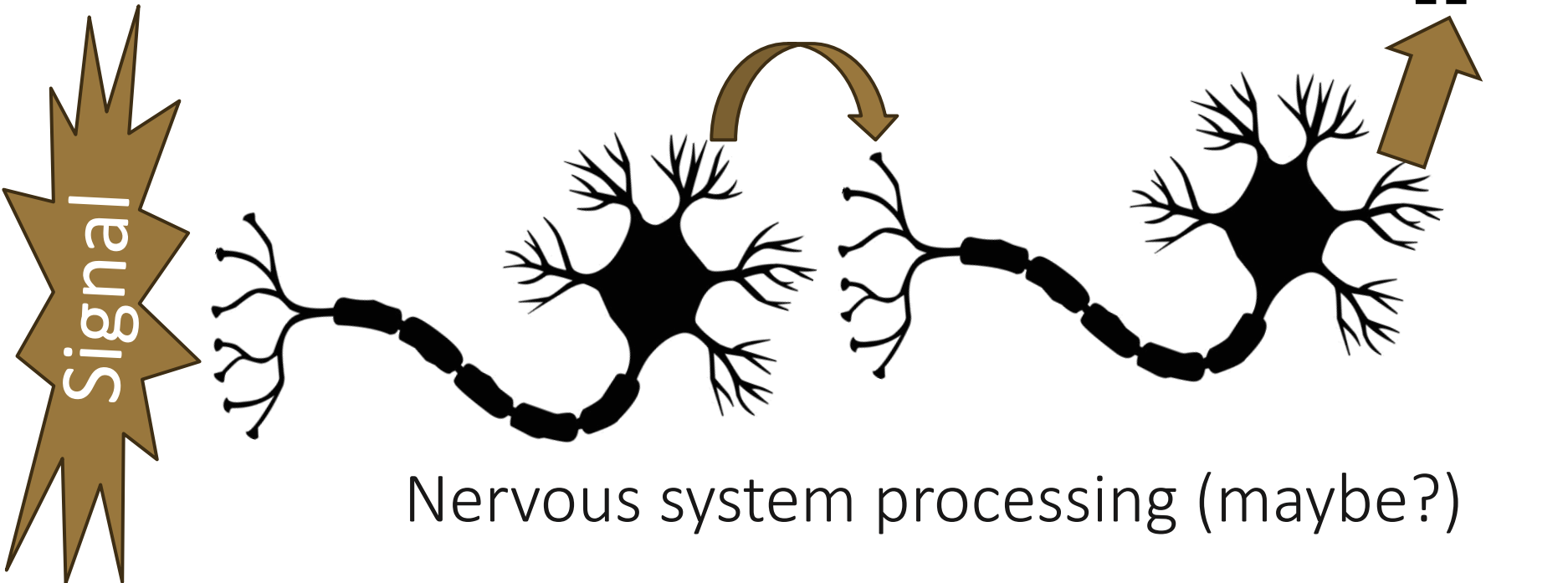
- Semi-supervised
  - Kind of a mix of supervised and unsupervised learning
  - We have some examples (labels), but not a lot
- Reinforcement learning
  - The computer makes decisions, then learns from those decisions
  - Based on action and rewards
  - Used for games. Playing against itself and learning from billions of decisions



# Examples

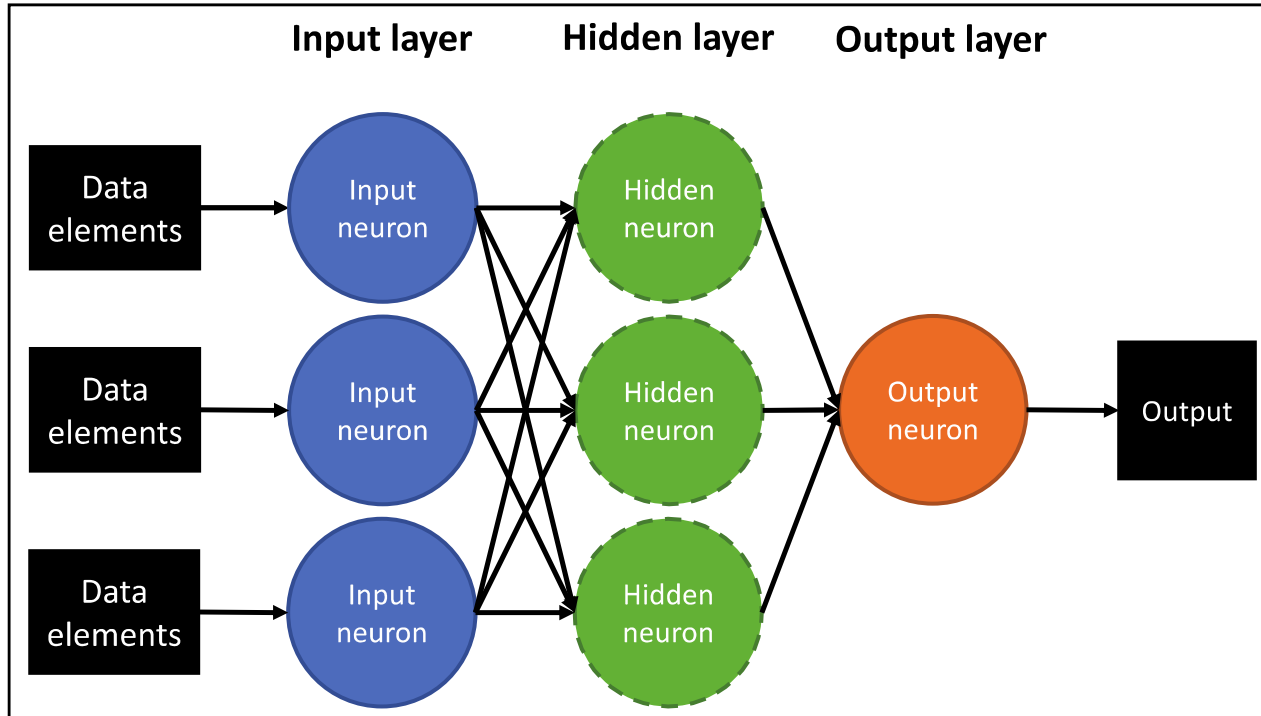
- Semi-supervised
  - Data analytics
  - Auditing and drug diversion
  
- Reinforcement
  - Identifying ideal treatment pathways
  - Mechanical ventilation
  - Reinforcement Learning from Human Feedback (RLHF) (generative AI)

# Neural Networks

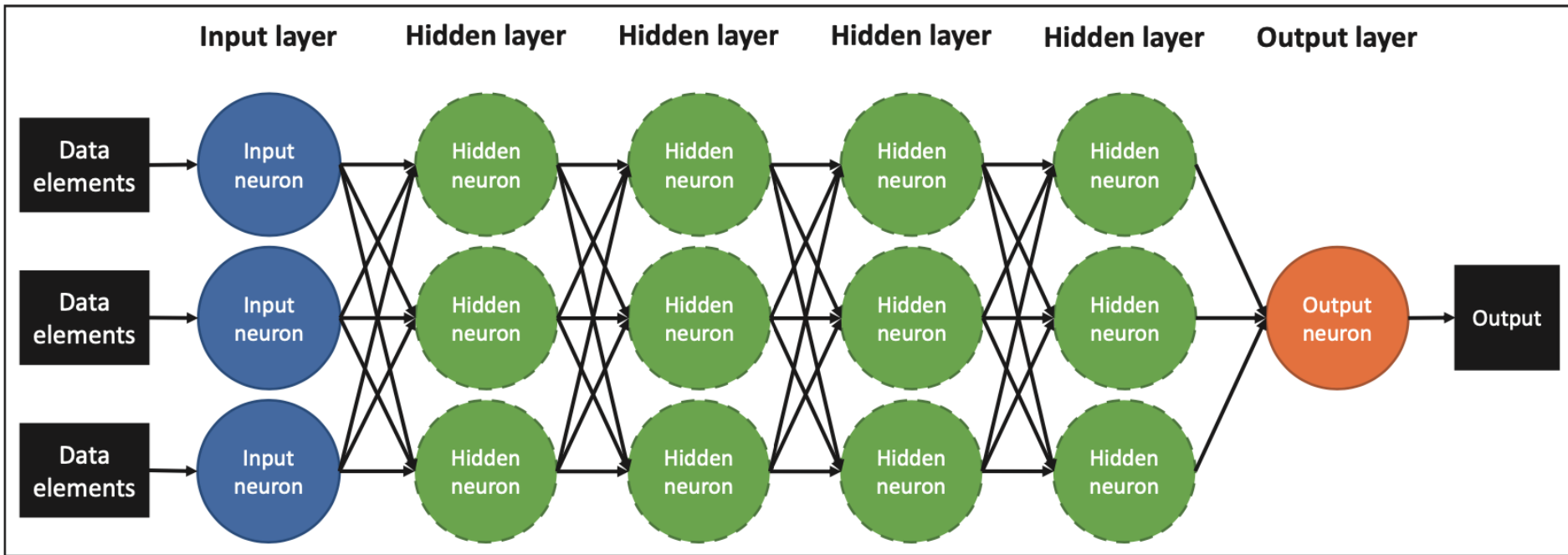


Nervous system processing (maybe?)

# Neural Network



# Deep learning



# Examples

- Image processing
- Natural language processing

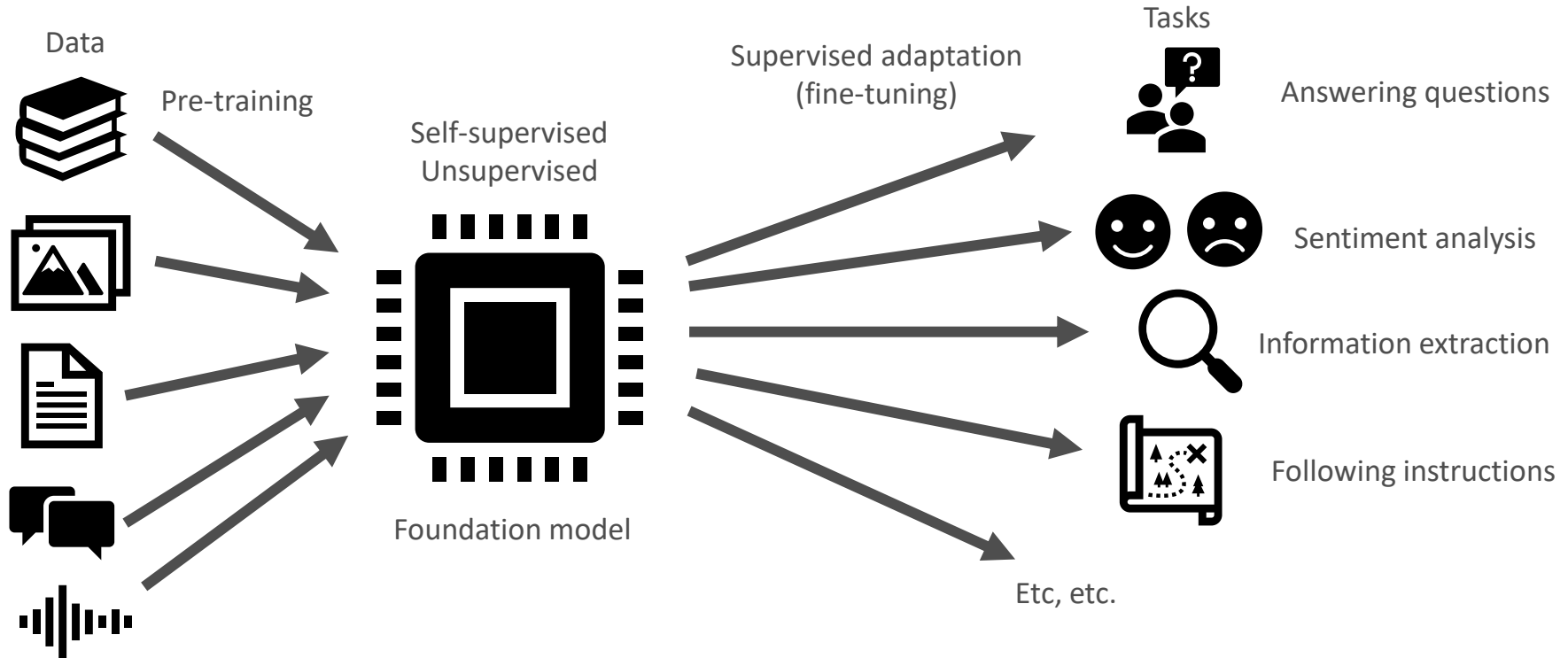


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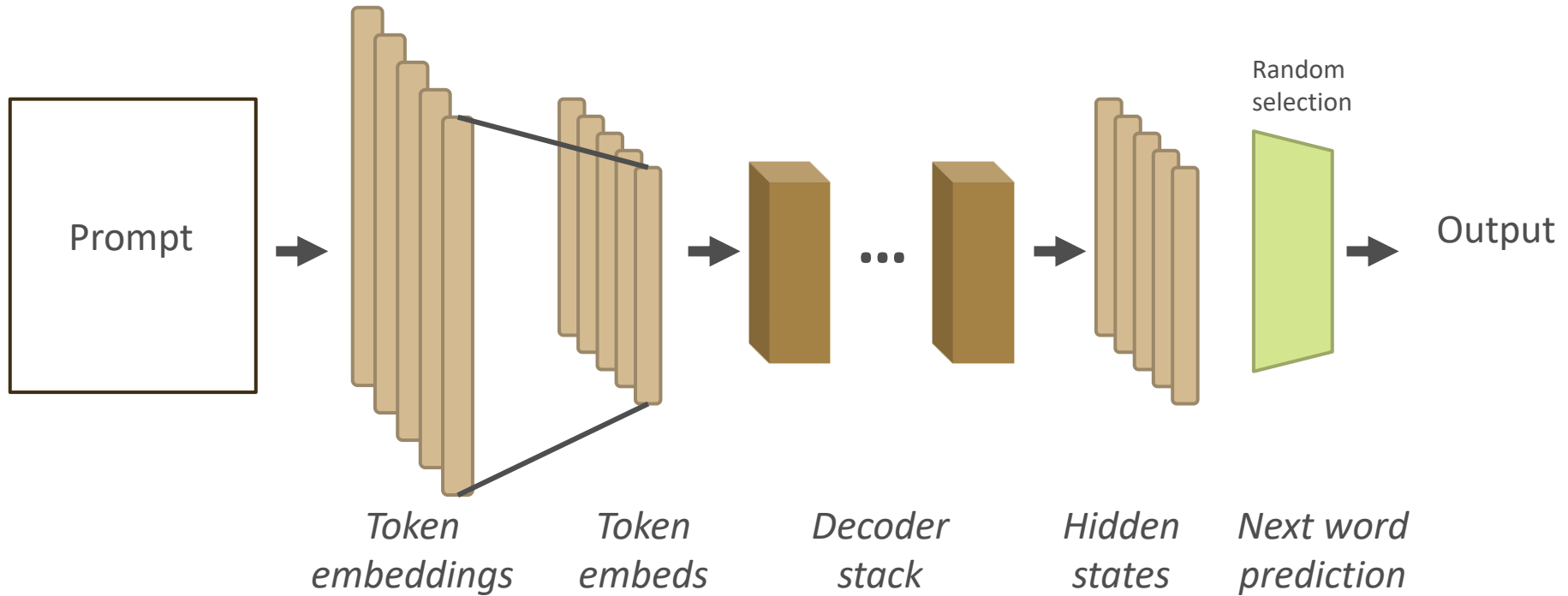


# Large Language Models (LLMs) - ChatGPT

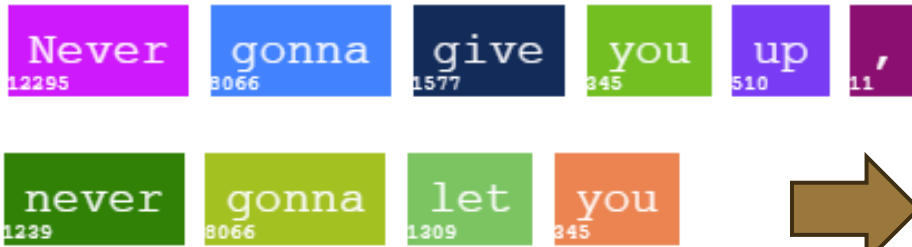
- Generative Pre-trained Transformer (GPT)



# Large Language Model (LLM) overview



# Never gonna give you up, never gonna let you...

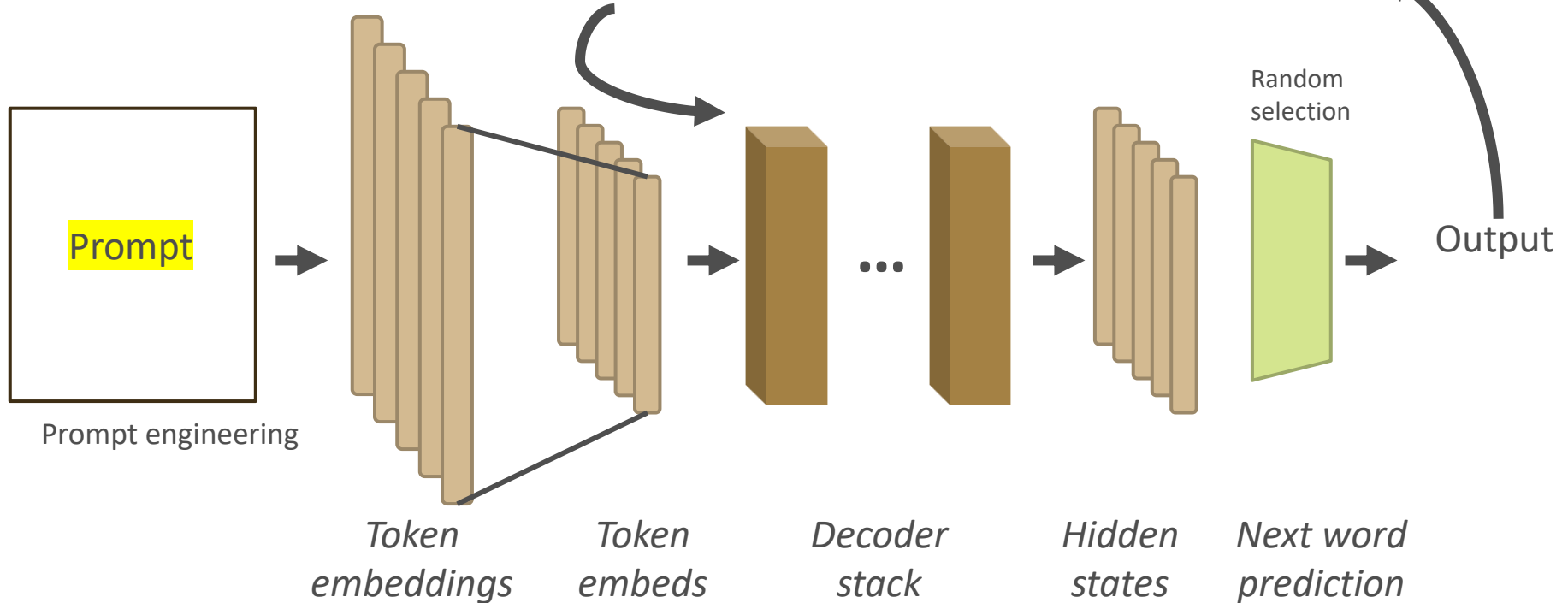


## Prediction

#	probs	next token ID	predicted next token
0	78.85%	866	down
1	12.69%	467	go
2	0.79%	651	get
3	0.68%	510	up
4	0.57%	503	out
5	0.54%	2666	leave
6	0.37%	2121	fall
7	0.30%	307	be
8	0.25%	4656	die
9	0.23%	1011	take

# How to improve the results?

Reinforcement Learning from Human Feedback (RLHF)



# Potential use cases

- Code generation
- Text summarization
- Text generation
- Conversational AI for patient support
- Speech recognition
- Image or text annotation
- Write clinic notes
- Writing a prior authorization letter, with supporting references
- Write notes to patients interpreting labs



pretend you are a doctor and interpret a lab result with an elevated TSH and low FT4



As a doctor, I would interpret a lab result showing an elevated TSH and low FT4 as indicating a potential thyroid dysfunction. The thyroid gland is responsible for producing hormones that regulate various bodily functions, including metabolism and energy production. TSH, or thyroid-stimulating hormone, is produced by the pituitary gland and stimulates the thyroid to produce its hormones. Elevated levels of TSH can indicate that the thyroid is not producing enough of its hormones, a condition known as hypothyroidism. Low levels of FT4, or free thyroxine, can also indicate hypothyroidism. It is important for individuals with hypothyroidism to receive proper treatment to prevent further complications.

Curtesy Yaa Kuma-Crystal



now write a message to your patient communicating those labs results



Dear patient,



I am writing to inform you that your recent lab results indicate a potential thyroid dysfunction. Specifically, your TSH levels are elevated and your FT4 levels are low. This can be indicative of a condition called hypothyroidism, in which the thyroid gland is not producing enough of its hormones.

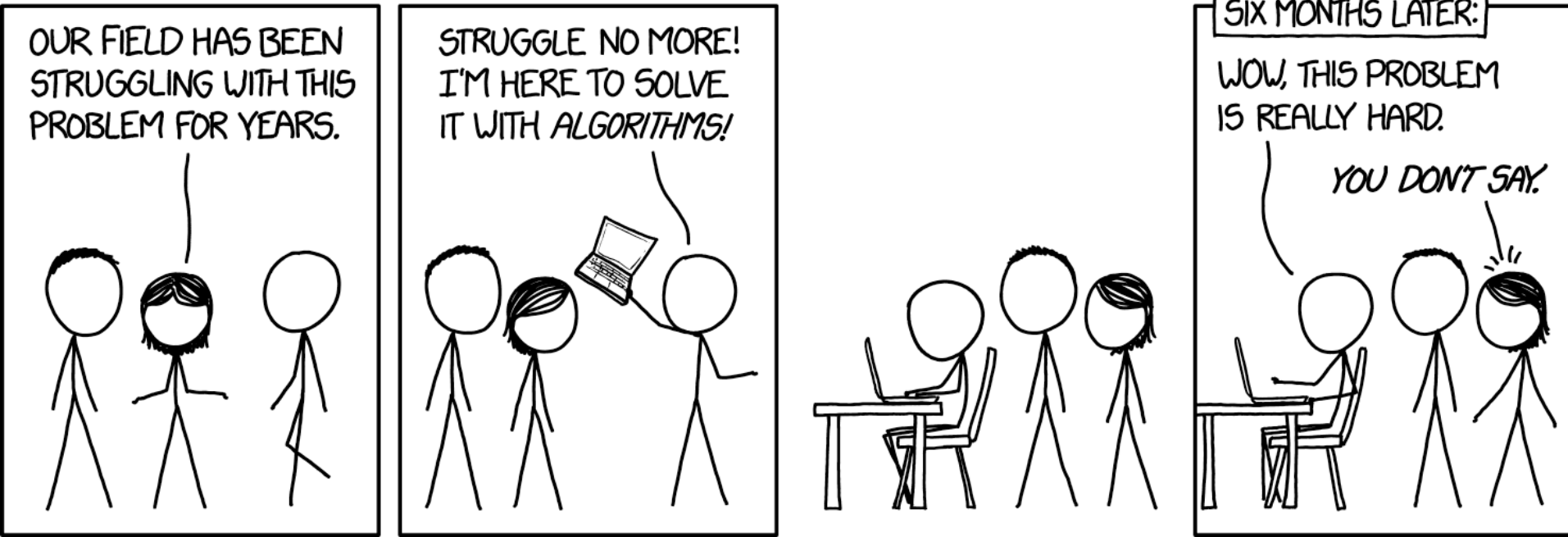
It is important to note that these results do not necessarily confirm a diagnosis of hypothyroidism. Further testing and evaluation will be needed to determine a proper diagnosis and course of treatment. In the meantime, it is important to monitor your symptoms and contact me immediately if you experience any concerning changes.

Curtesy Yaa Kuma-Crystal



# Considerations in healthcare

# AI models will solve all our problems!



<https://xkcd.com/1831/> Creative commons

# Truth

- Health care is incredibly complex
- “All models are wrong, but some are useful”  
– George Box
- The ultimate decisions are in the hands of the patients and caregivers
  - They have the additional context that is required and making these sometimes difficult decisions

# More than just a score...


- What are the next steps someone should take?
- What is the expected outcome or workflow?
- What factors went into producing the score?
- Models must be trained/calibrated on local data
  - External validation

People – Process – Technology!

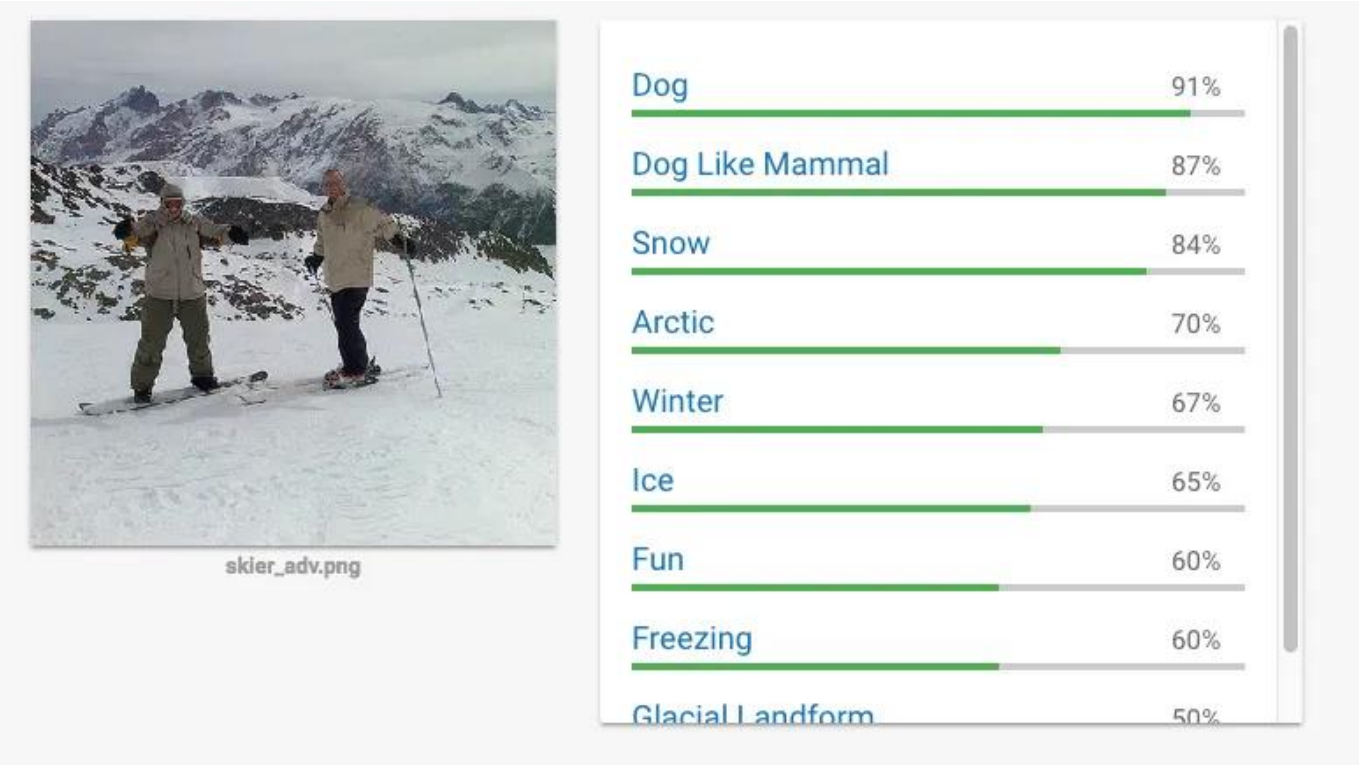
# Model drift

- The performance of a model degrades over time as the environment changes
  - Relationships between variables change over time
  - The underlying data could change
  - Clinical practice changes
- The model must be recalibrated
- Have a long-term maintenance plan
  - Consider when to remove/retire the model



 DALL-E 3

# AI hallucinations



# AI hallucinations



Dall-E 2. Image  
source: [OpenAI](#)

# Large Language Models (LLMs) - ChatGPT

- AI hallucination
  - A *confident* response by AI that is not true
    - Cannot be grounded on any data ever accessed or trained on
  - Generates false information
  - Predictive text

AI-generated suggestion for identifying immunocompromised patients:  
“add biologic agents, such as adalimumab, **etanerfigut**, and golimumab,  
which are used to treat autoimmune disorders.”



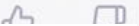
# Myth or fact??



Write a clinic note about a patient with diabetes that is not compliant



Patient is a 50-year-old female with a history of type 2 diabetes mellitus. She has been non-compliant with her diabetes management, including not taking her prescribed medications and not following a proper diabetic diet. She has also not been regularly monitoring her blood sugar levels. As a result, she has experienced increased glucose levels and symptoms of uncontrolled diabetes, such as frequent urination and fatigue. It is important for the patient to improve her compliance with her diabetes management in order to prevent potential complications and improve her overall health.



Curtesy Yaa Kuma-Crystal

More data => better AI!



# Truth

- AI is only as good as the data it trains on or ingests



- Labeling large amounts of data is very difficult
- Beware of model bias (fairness metrics)

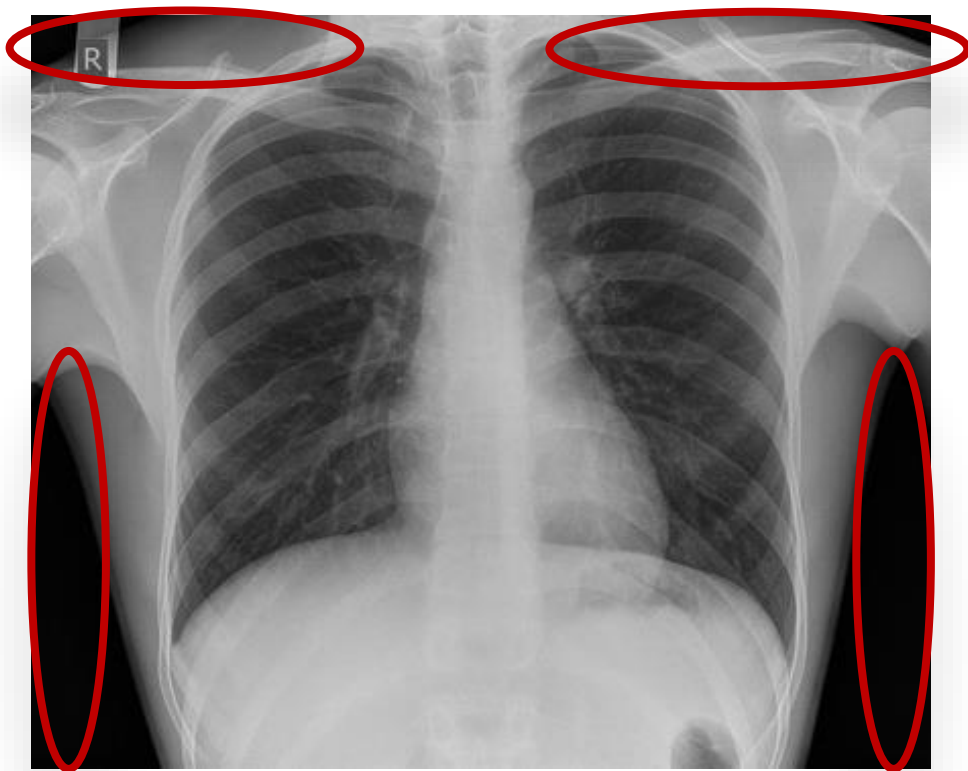
# Shortcuts in the training data

- Researchers developed a model to identify if cows were in the picture or not



Recognition in terra incognita. In *Proceedings of the European conference on computer vision (ECCV) 2018*. pp. 456-473

# In healthcare – AI for COVID-19 in CXR



High performance at one hospital  
Failed at another health system

Saliency maps showed that laterality  
markers were important features

# Model Bias

- Background
  - Researchers discovered significant disparities in diagnostic accuracy for skin conditions across skin tones
    - Less accuracy when diagnosing conditions in **darker skin tones**
  - Researchers developed a deep learning model to provide decision support and enhance accuracy, particularly for darker skin tones
    - The model was tested with dermatologist and primary care providers (PCPs)

# Model Bias

- The model successfully improved accuracy for both dermatologists and PCPs
  - Dermatologists saw a **33% improvement** in diagnostic accuracy
  - PCPs experienced an **impressive 69%** improvement
- Impact on disparities
  - Disparities **persisted** among dermatologists across skin tones
  - Surprisingly, disparities across skin tones **increased by 5%** for PCPs

# AI Recognition of Patient Race in Imaging

- Deep learning models detecting race from medical images
  - X-ray, CT, and mammography from various body sites
  - Chest, spine, breasts, lungs, and hand
- Model predicted self-reported race with AUC 0.90
  - Attempted to control for BMI, disease distribution, breast density, etc.
  - Then corrupted, cropped, and noised the images
- **Model could still detect race in images when experts couldn't**



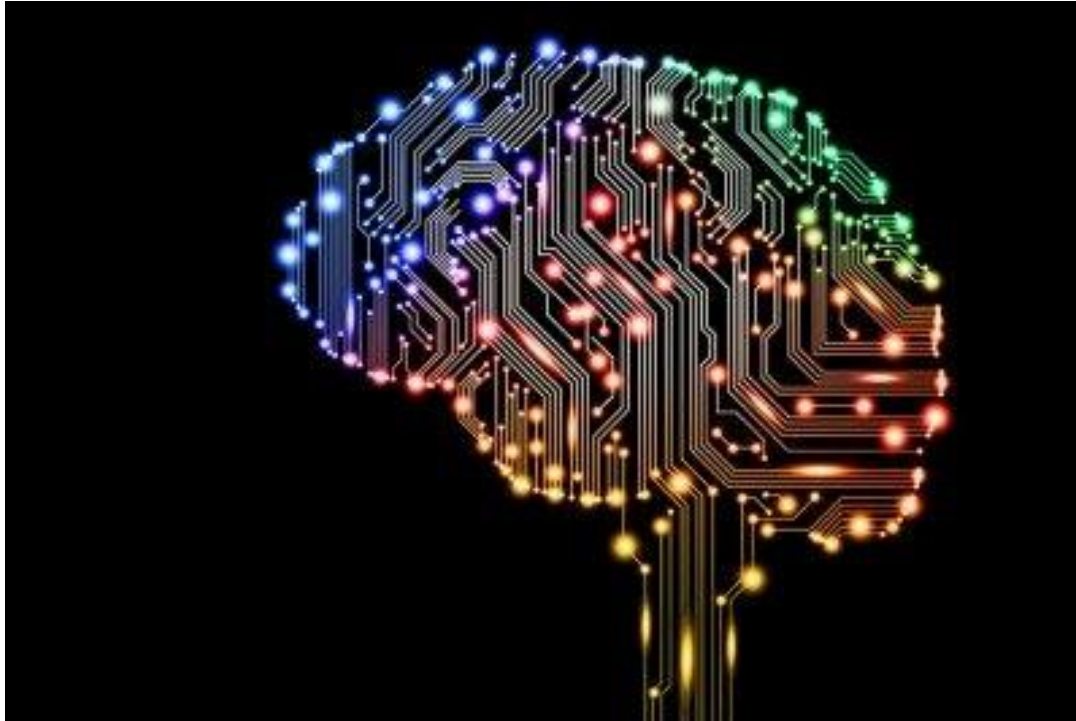
# Healthcare Data is Biased

- Researchers used a commercially available model to identify patients with the greatest care needs for referral to care management programs
- At the **same risk score**, Black patients had:
  - 26% more chronic illnesses
  - More uncontrolled hypertension and higher SBP
  - Higher HbA1c values
  - Higher serum creatinine levels
  - Higher LDL levels

# Healthcare Data is Biased

- Sex and gender bias
  - Differences in physiological markers and disease prevalence
    - Cardiovascular disorders, cancer, autoimmunity, diabetes, etc.
    - Men and women respond differently to treatments
      - i.e. statins, ACE inhibitors, beta-blockers, etc.
  - Differences in data representation
    - i.e. coronary heart disease is the leading cause of death in women, but the majority (67%) of patients in clinical trials are men.

# Will AI will take over my job?



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# Truth: AI = “Augmented Intelligence”

- Pharmacists excel at:
  - Common sense
  - Compassion
  - Context
  - Dilemmas
  - Morals
  - Imagination
  - Abstraction
  - Generalization
- AI systems excel at:
  - Pattern identification
  - Endless capacity
  - Natural language processing
  - Locating knowledge
  - Machine learning
  - Minimizing bias

“The rise of machines has to be accompanied by heightened humaneness — **with more time together, passion and tenderness** — to make the ‘care’ in healthcare real”  
- Eric Topol

Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again (2019)



Weird Ai Generations

@weirddalle



Everyone: AI art will make designers obsolete

AI accepting the job:



# Balancing excitement and safety

- Some AI models have shown improvements in mortality and patient outcomes
- Many have not, and most fail to make it to clinical practice
- Some AI models have even increased mortality!
  - Model for predicting AKI



*BMJ.* 2021;372:m4786. PMID:33461986



DALL-E 3

# Analogy to medications

Phase 0 – Needs assessment

Phase 1 – Algorithm training

Phase 2 – Evaluation by end users

Phase 3 – Clinical trial

Phase 4 – Post-deployment  
surveillance



# Regulations

- FDA - Software as a Medical Device (SaMD)
  - “Software intended to be used for one or more medical purposes that perform these purposes without being part of a hardware medical device.”
- Good Machine Learning Practice (GMLP)
  - Jointly by USA FDA, Health Canada, and the United Kingdom’s Medicines and Healthcare products Regulatory Agency (MHRA)
  - 10 guiding principles

The best way  
to predict  
the future is  
to build it!



# Building the future: Key considerations

- How does the use of ML/AI affect pharmacy practice?
  - Examine Board of Pharmacy rules
  - Are there things that can be safely delegated to ML/AI models?
- **Humanize care and address burnout**
  - AI to bring joy to healthcare work, not do more complicated tasks
  - Assure that “normal” is still in the human workflow
- **Focus on the human-AI team**
  - “Augmented intelligence”

# Building the future: Key considerations

- Project identification and prioritization
  - Where should resources focus?
  - Pharmacists understand the workflows
- Assure AI in healthcare is safe, efficacious, **and equitable**
  - Support equity and fairness metrics
- ML/AI (and healthcare) are rapidly evolving!
  - Consider maintenance and updating policies

# Key Takeaways

1. AI describes a computer system's ability to perform a task that would normally require human cognition.

Example: perception, learning, vision, etc.

Very powerful tool, but also has limitations

2. Humans + machines

Focus on the power of the combination!

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