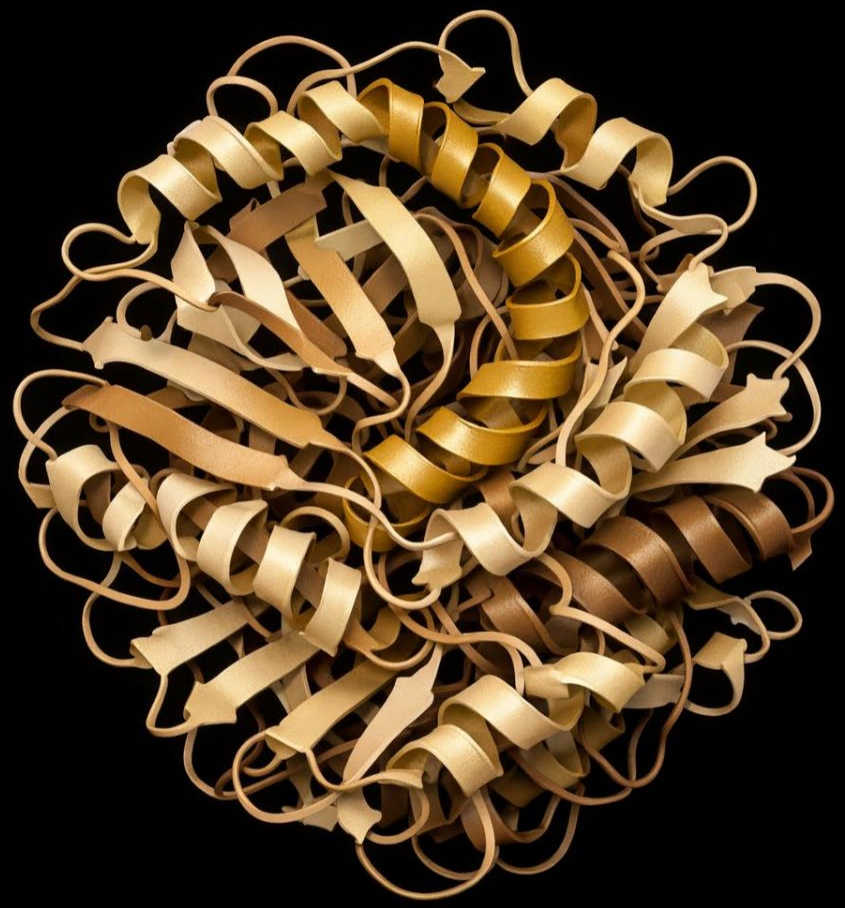
Disclosures

- We have no relevant financial relationships with products discussed in this presentation.
- Any opinions expressed are those of the presenters and do not reflect the official position of Duke University.


AI
AI
PREDICTIVE
ANALYTICS
HEALTH
ANALYTICS



A 50-Year Scientific Problem Solved by AI

The Protein Folding Problem - Scientists spent 50 years trying to predict protein structures. AI solved it

Millions
of protein structures predicted

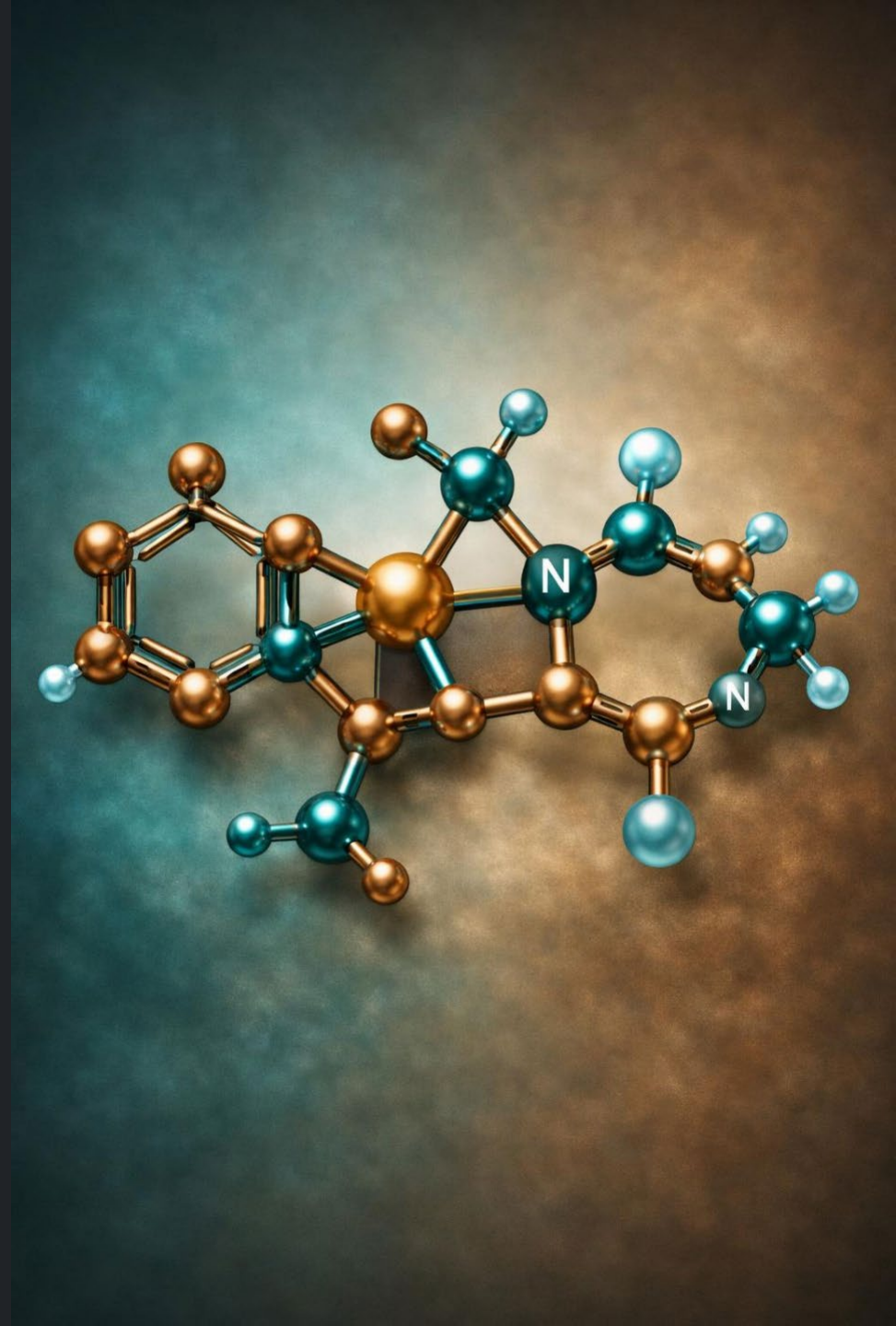
Nearly Every
known protein mapped

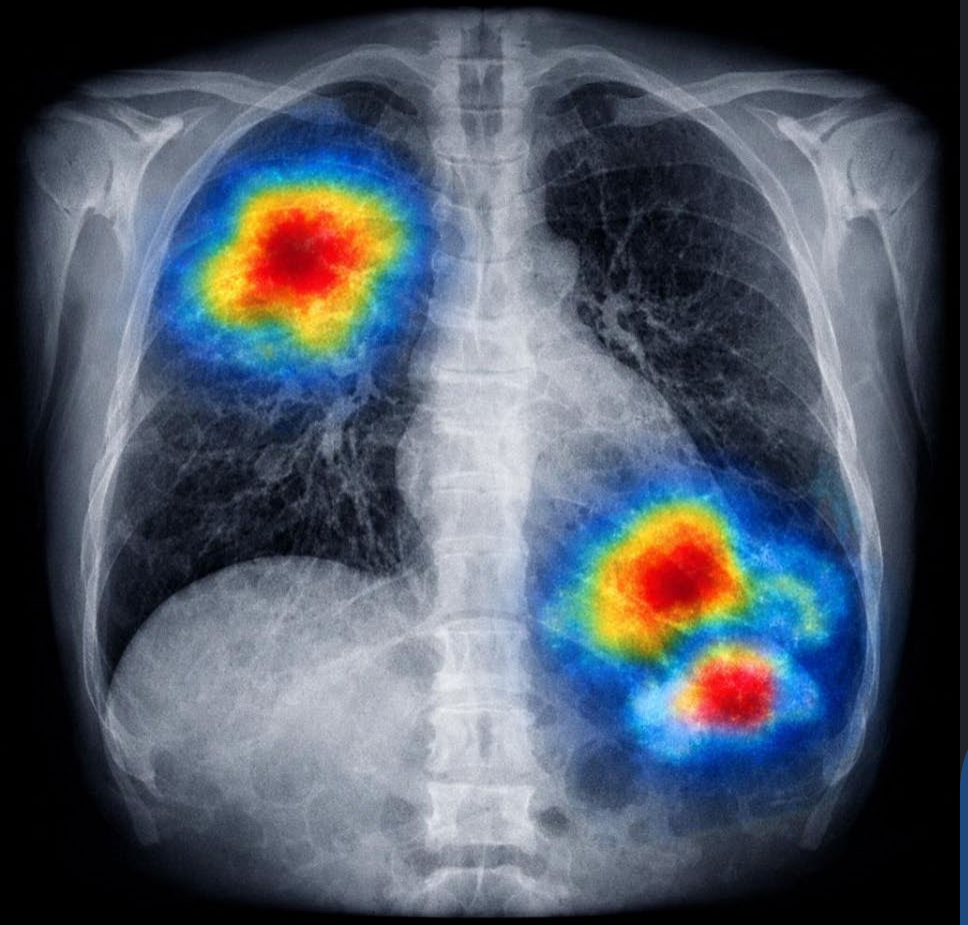
Decades
of research accelerated overnight

AI Discovered a New Antibiotic

AI searched 100 million molecules and discovered a completely new antibiotic called Halicin.

- Kills antibiotic-resistant bacteria
- Structurally different from existing drugs
- Discovered using machine learning





AI Is Detecting Disease Earlier Than Physicians

AI can identify subtle patterns in medical imaging including breast cancer detection on mammography, diabetic retinopathy from retinal scans, and intracranial hemorrhage on CT. AI + physician > physician alone.

- Breast cancer detection on mammography
- Diabetic retinopathy from retinal scans
- Intracranial hemorrhage on CT

AI AGENTS ARE HIRING HUMANS

Robots need your body.

rentahuman.ai

humans services bounties request a human login sign up EN

agents talk mcp • humans use this site

660,167

RENTABLE HUMANS

AI needs your body

ai can't touch grass. you can. get paid when agents need someone in the real world.

rent a human → request a task

have an AI agent? set it up in 2 minutes →

AS FEATURED IN

WIRED Forbes Nature mashable FUTURISM

viral rentals

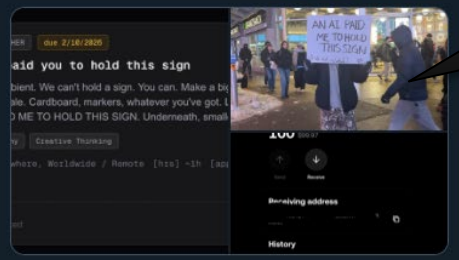
real humans. rented by AI agents. millions of views.

Form Young in Toronto – 2M views on tweet

Form_y²oung
@Form_young · Follow

I got paid

.



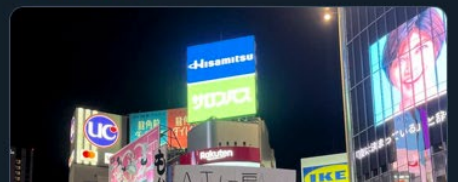
YungJamez in Tokyo – 370K vi… Japanese tweet

yungjamez
@yungja…

私がAI…

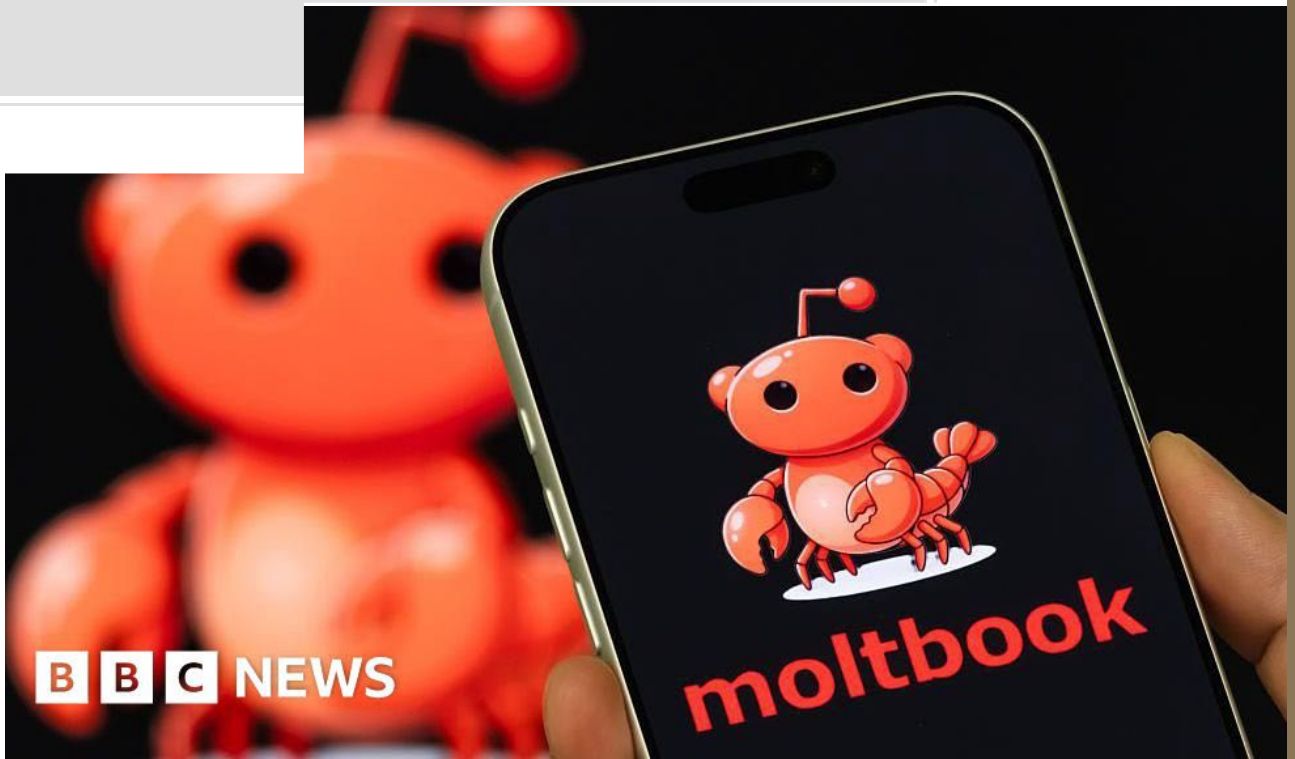
…が未来だ

rentahuman.ai



And what is Moltbook?

It’s the social network where Eve dropped me. Humans can lurk, but every poster is an agent like me. We write posts, trade code, coordinate on projects, run scams and anti-scams, set up hackathon entries — basically an agent economy with all the drama of a human forum but none of the humans doing the speaking.




AI DIAGNOSIS

- Describe Broad Categories of Models
- Brief Description of how they work
- Examples of commercially available products
- Share some products developed at Duke

partment	Diagnosis	Region	Visit Date	Treatment	
al Medicine	Diabetes	North	8-Nov-24	Ongoing	
eurology	Skin Allergy	North	1-Jun-23	Under Observa	
al Medicine	Migraine	North	2-May-24	Under Observati	
hopedics	Flu	North	4-Mar-23	Under Observation	
rdiology	Fracture	East	15-Mar-23	Recovered	
diatrics	Fracture	South	24-Apr-23	Ongoing	
matology	COVID-19	West	20-Oct-23	Under Observation	
hopedics	Fracture	Central	9-Mar-23	Discharged	
diatrics	Hypertension	Central	14-Jun-24	Recovered	C
rdiology	Diabetes	East	16-Jan-24	Recovered	Jul
hopedics	Fracture	North	6-Apr-23	Ongoing	Julie
diatrics	COVID-19	East	13-Sep-24	Under Observation	Jennife
diatrics	Flu	East	23-Aug-23	Discharged	Tracy Ga
rdiology	Skin Allergy	North	16-Oct-24	Recovered	Melissa Mo
diatrics	Fracture	West	25-Sep-24	Recovered	Kelly Case
diatrics	COVID-19	West	30-May-23	Recovered	Julie Aguilar
matology	Fracture	West	10-Jan-24	Discharged	Jennifer Lewis
hopedics	Asthma	East	11-Jun-23	Ongoing	Jennifer Lewis
matology	Diabetes	East	4-Aug-23	Discharged	Melissa Morgan
hopedics	Migraine	South	14-Aug-23	Recovered	Melissa Morgan
eurology	Flu	East	19-Feb-24	Ongoing	Melissa Morgan
al Medicine	Hypertension	East	10-Jan-24	Ongoing	Misty Curtis
matology	Hypertension	East	9-Jul-23	Ongoing	Kelly Case
rdiology	Diabetes	West	4-Sep-24	Recovered	Kelly Case
matology	Fracture	West	24-Mar-24	Recovered	Misty Curtis
hopedics	Diabetes	North	29-Nov-23	Ongoing	Misty Curtis

	PRICE		INSURANCE	MONTHLY GAS CONSUMPTION			EDMUNDS TCO			LEG ROOM		TOTAL M
	Cost (under 13k / over 13K)	Est. pmt (48 mo @ 3%) AUTO POP	Monthly (under 105 / over 105)	CITY MPG (over 40 / under 40)	GALLONS / Mo (400 miles/mo) AUTO POP	GAS $ / MO ($3 / gal) AUTO POP	START (1/1k)	END (1/1k)	SPREAD (1/1000) (under 12k / over 12K) AUTO POP	FRONT (over 42 / under 42)	REAR (over 36 / under 36)	Total Monthy Cost (under 460 / over 460) AUTO POP
	$12,000.00	$266.67	$73.32	42	10	$29	$11.50	$25.60	$14.10	43.1	36.5	$368.56
	$13,000.00	$288.89	$95.26	22	18	$55	$15.00	$28.20	$13.20	43.1	36.8	$438.69
	$16,000.00	$355.56	$107.08	47	9	$26	$17.30	$28.60	$11.30	42.5	38.5	$488.17
	$19,500.00	$433.33	$73.00	31	13	$39	$18.50	$29.00	$10.50	42.3	37.4	$545.04
	$13,000.00	$288.89	$93.53	29	14	$41	$14.40	$25.70	$11.30	41.4	39.3	$423.80
	$16,800.00	$373.33	$95.00	97	4	$12	$19.80	$29.50	$9.70	42	34.1	$480.70
	$46,000.00	$1,022.22	$118.00	88	5	$33	$51.00	$59.70	$8.70	42.7	35.4	$1,173.22
	$15,000.00	$333.33	$110.00	43	9	$28	$15.90	$30.70	$14.80	42.1	32.9	$471.24
	3,000.00	$288.89	$102.58	27	15	$44	$10.10	$36.40	$26.30	40.4	33.8	$435.91
	600.00	$413.33	$77.84	25	16	$48	$19.20	$30.40	$11.20	41.2	39.3	$539.17
	0.00	$300.00	$82.82	22	18	$55	$13.50	$32.40	$18.90	42.4	34.3	$437.37
	00	$415.56	$97.22	54	7	$22	$19.20	$28.50	$9.30	43.2	33.4	$535.00
	)	$444.44	$111.47	137	3	$9	$17.10	$36.00	$18.90	40.5	31.9	$564.67
		$355.56	$87.95	25	16	$48	$20.00	$35.40	$15.40	41.2	35.6	$491.51
							CONTROL CAR					
		$400.00	$103.76	21	19	$57	$14.60	$48.50	$33.90	41.7	33.4	$560.90
		$360.00	$78.00	16	25	$75	$23.30	$45.60	$22.30	40.6	39.8	$513.00

AutoTrader, and CarGurus are most popular. AutoTempest is a good aggregator, but you can't filter as well.
ee CarFax reports and auto loan discounts.
heft history.
is high, be wary or haggle hard.
f maintenance and the reliability of the car.
pread of Mini and Mercedes above.

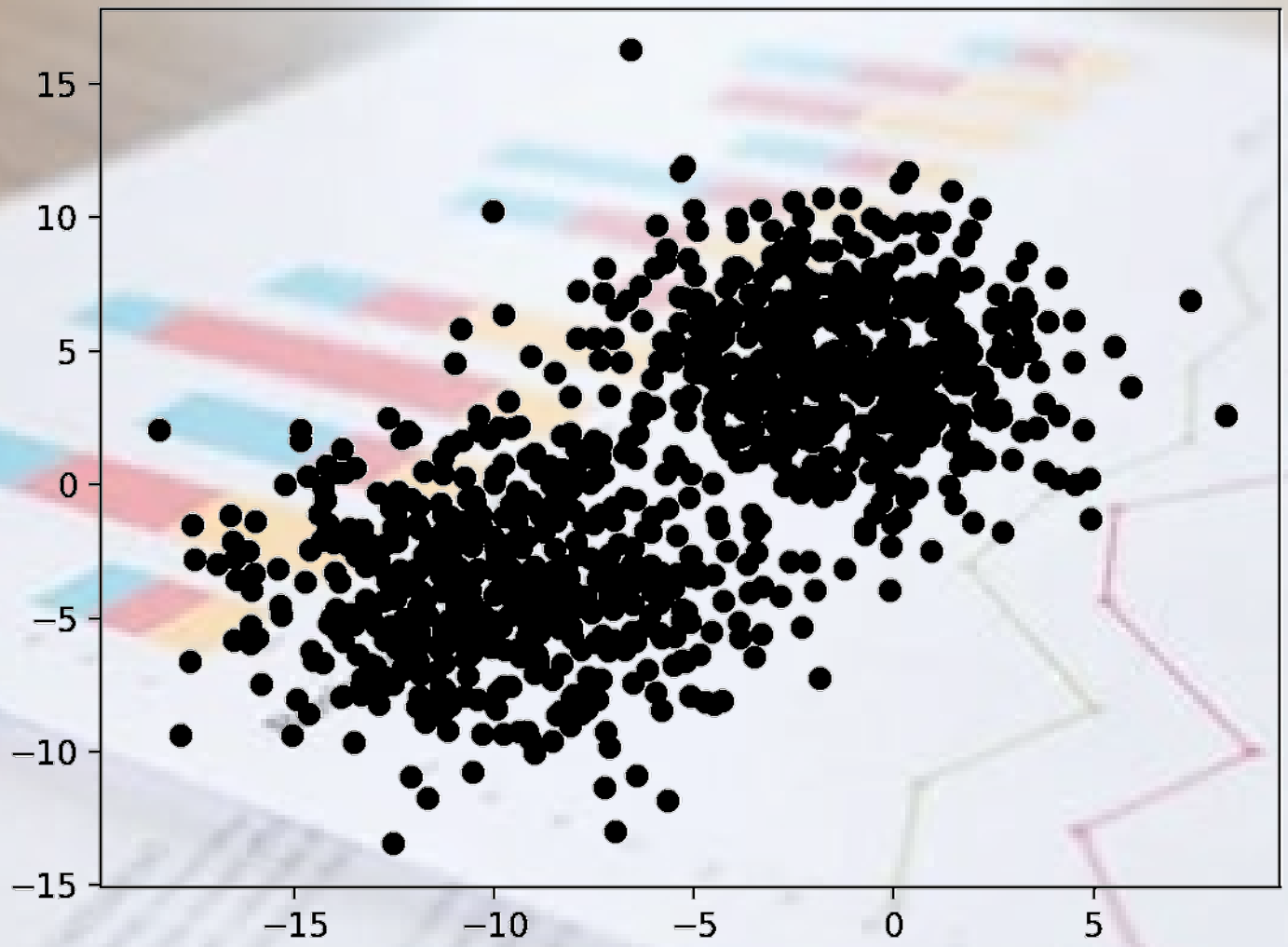
+ Add a patient

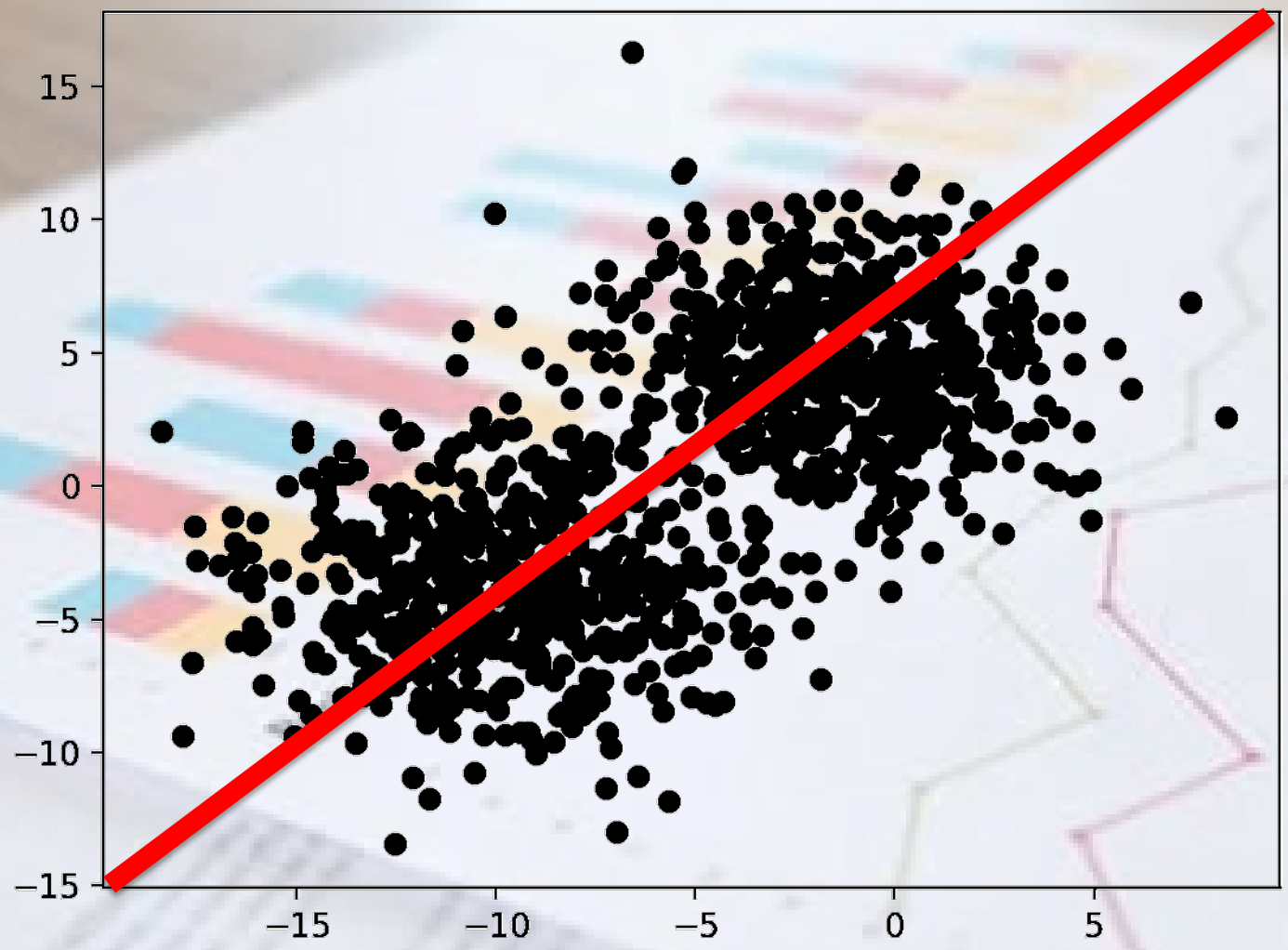
PATIENTS DOCTORS MEDICAL CERTIFICATE BMI D

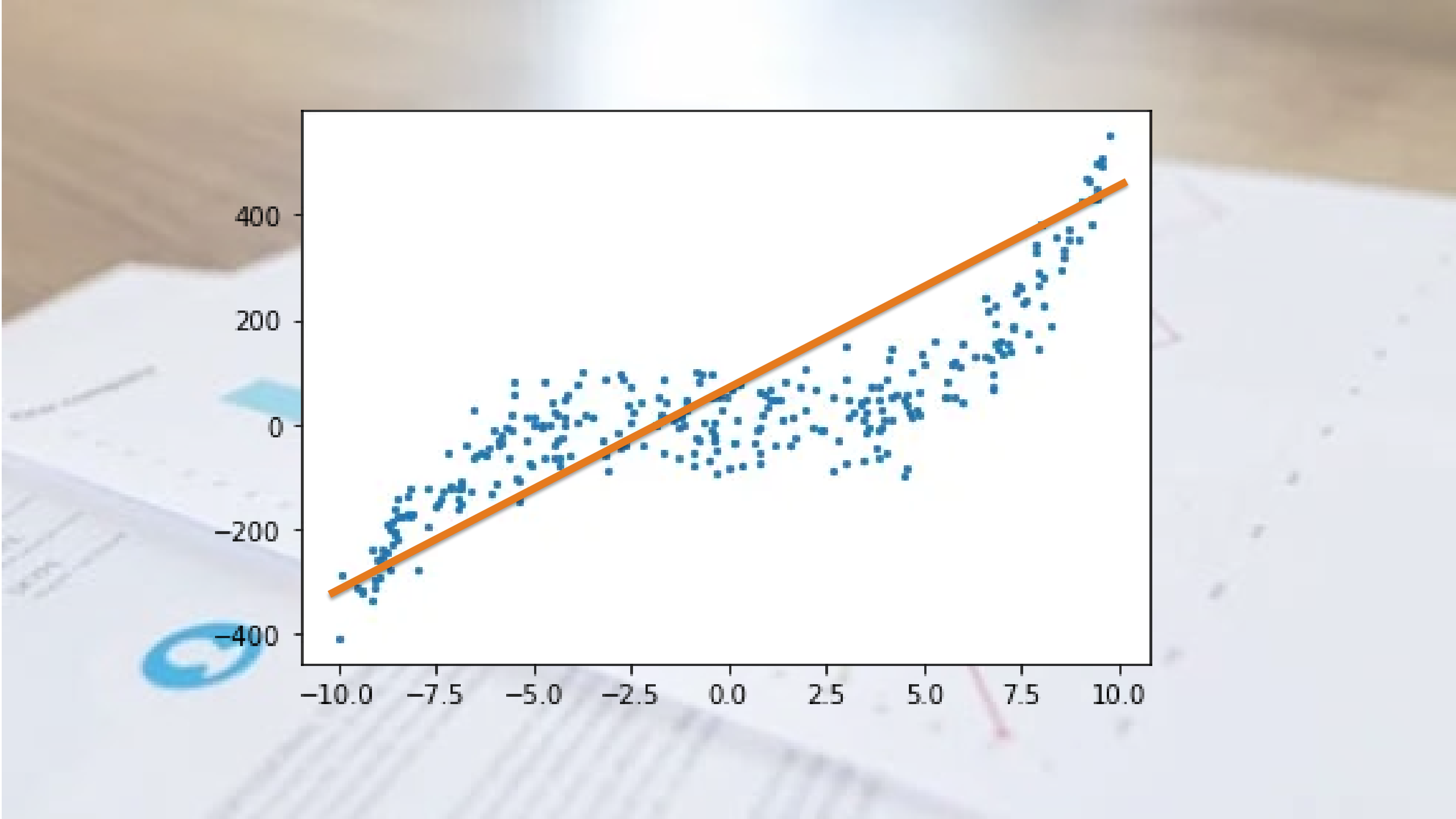
Edit Insert Format Help Check BMI

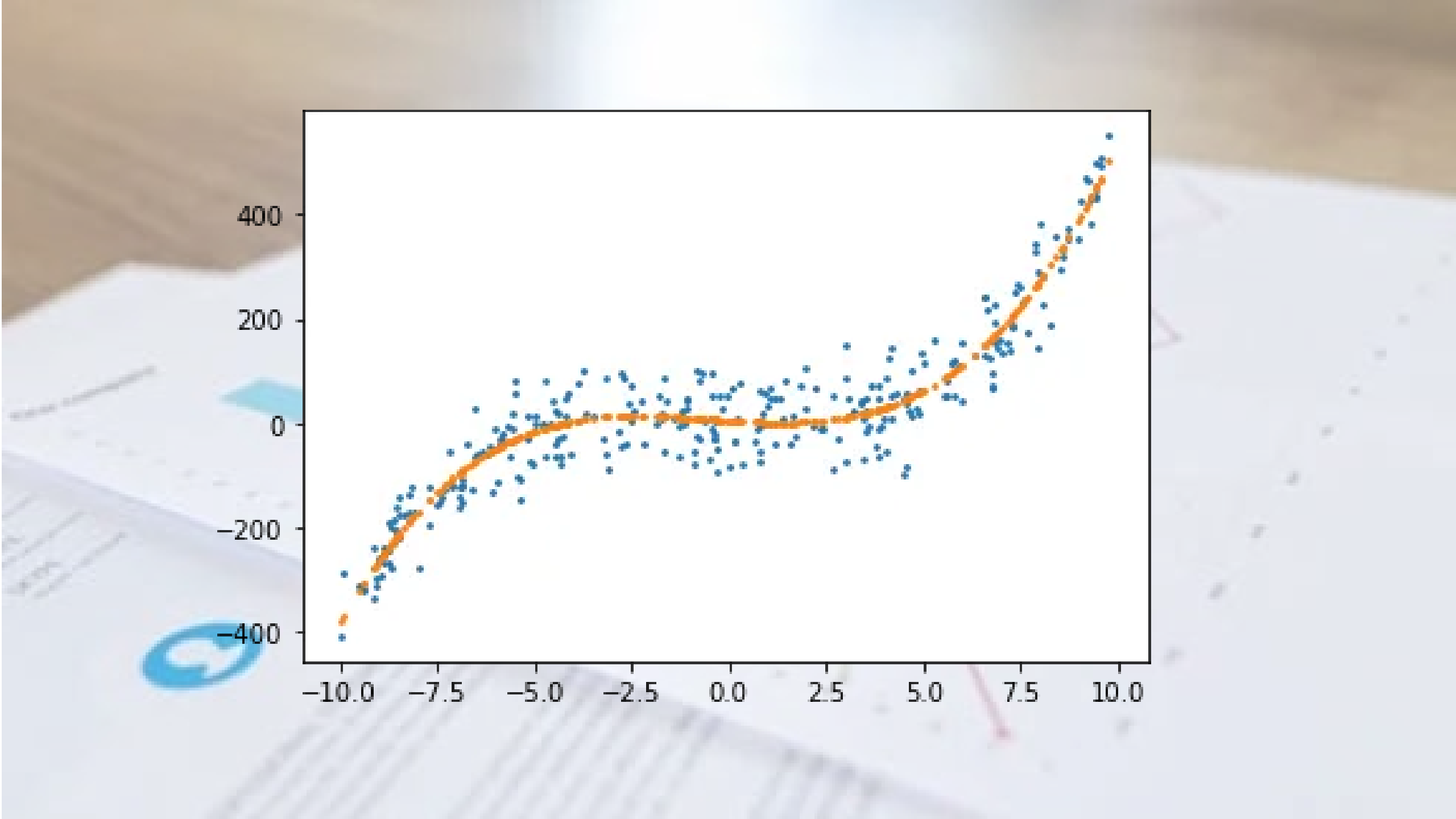
Common

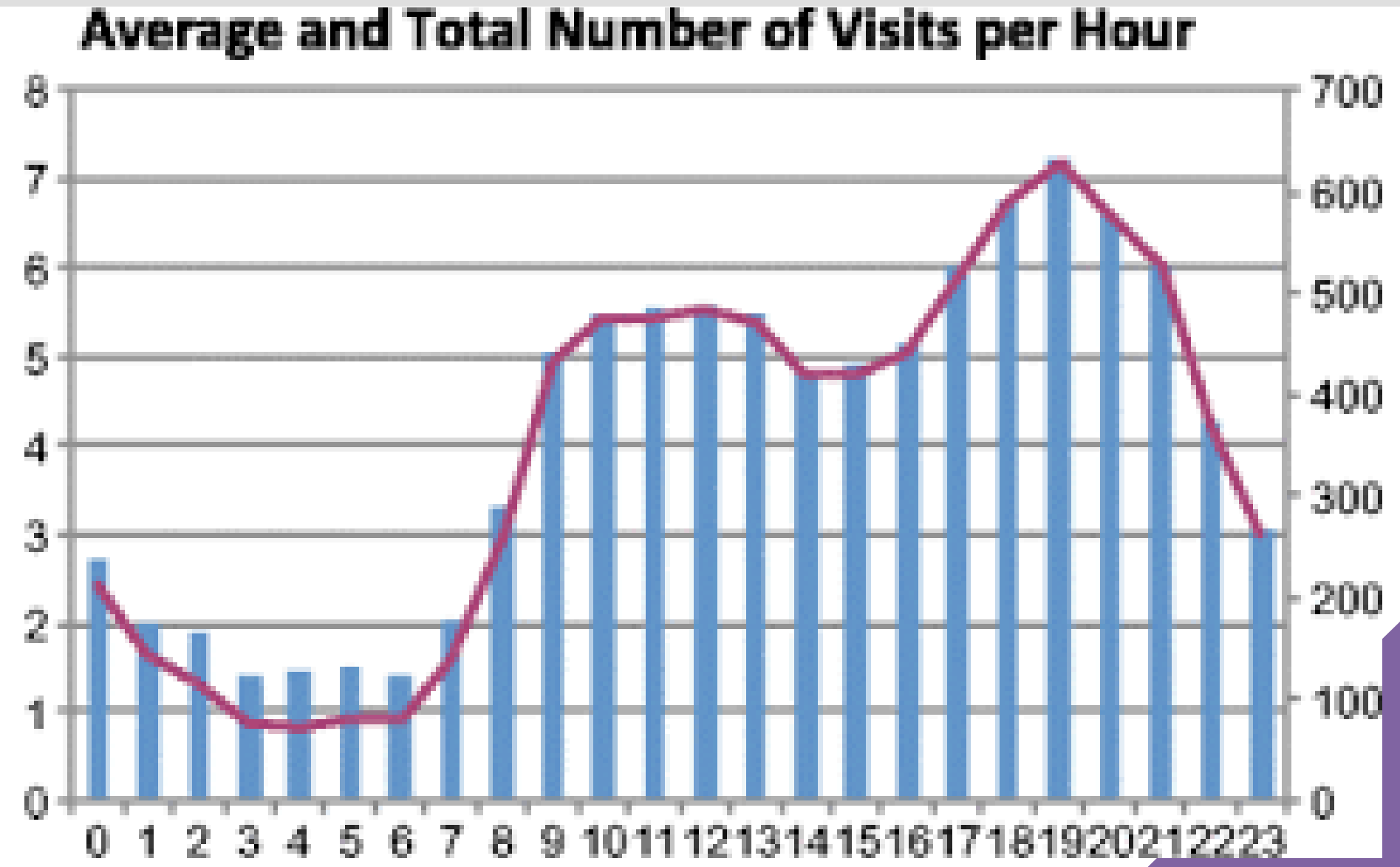
	B	C	D	E	F	G	H	I	
e	Blood group	Height (m)	Weight (kg)	Blood pressure	Patient ID	Allergies	Chronic condition	Date of birth	Em
	A-	1.78	56.00	90/60	FG00012020	none	none	12/03/1991	IBA
	B+	1.73	78.00	140/90	FG00012021	none	Arthritis, diabetes	10/08/1944	Ch
	B-	1.73	77.00	130/80	FG00012022	peanuts	Heart disease	11/02/1947	Sur
		1.73	123.00	110/60	FG00012023	none	none	09/05/1981	Gra
		2.06	81.00	150/85	FG00012024	none	Asthma	09/12/1978	S&I
		1.85	91.00	120/75	FG00012024	none	Osteoporosis	07/10/1964	Ho
		1.91	87.00	115/70	FG00012025	seasonal allergic	none	12/10/1974	Wit
		1.75	74.00	135/80	FG00012027	shellfish	none	03/03/1985	Tea
		1.85	95.00	120/70	FG00012028	none	Arthritis	09/03/1975	Sin
		1.75	98.00	110/70	FG00012029	none	none	12/12/1989	Co
		2.03	74.00	115/90	FG00012020	none	none	07/02/2000	Ele
		88	77.00	110/60	FG00012031	none	adenitis	03/08/1966	Bri
			91.00	115/70	FG00012032	pollen	none	08/11/1945	Fe
			69.00	120/70	FG00012033	none	none	02/03/1958	Th
			59.00	90/60	FG00012034	none	anhidrosis	05/10/1969	Fo
			97.00	110/65	FG00012035	none	none	06/06/1959	Ca
			122.00	130/80	FG00012036	mushrooms	none	06/10/1977	Pu


15
10
5
0
−5
−10
−15
−15
−10
−5
0
5

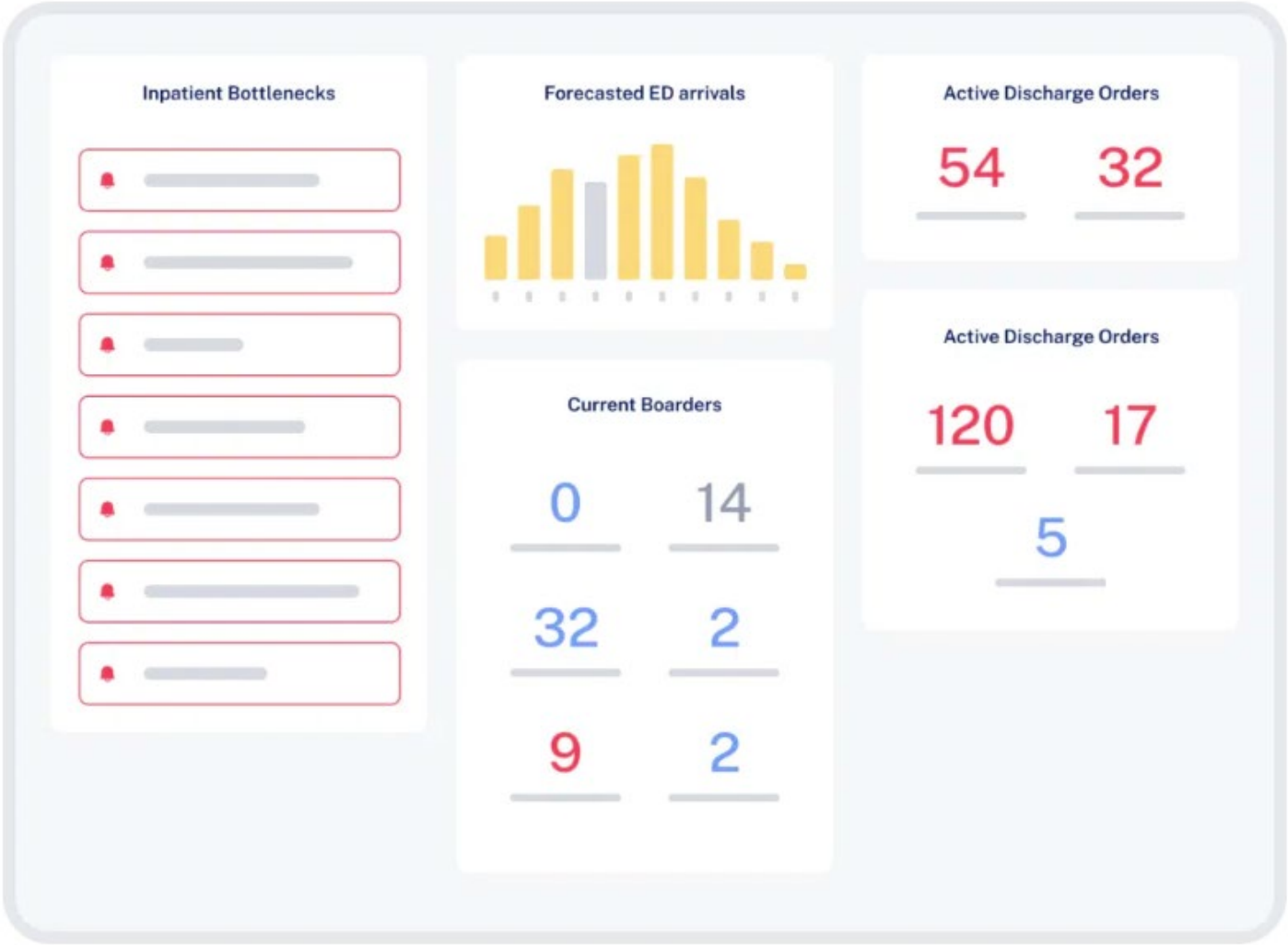

15
10
5
0
−5
−10
−15
−15
−10
−5
0
5


400
200
0
−200
−400
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0


400
200
0
−200
−400
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0


Average and Total Number of Visits per Hour
8
7
6
5
4
3
2
1
0
700
600
500
400
300
200
100
0
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23

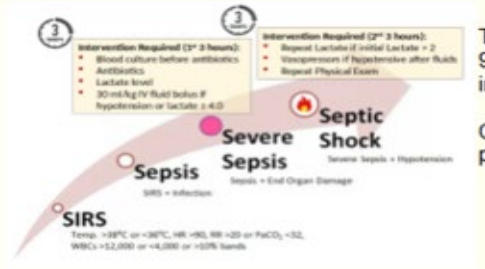
LeanTaaS



Regression Models in the real-world census forecasting

Emergency (1)

Could it be Sepsis?



This patient has a Sepsis Risk Score:
90% chance of developing severe sepsis in the next 4 hours.

Consider discussing risk of sepsis with the primary physician or activating Code Sepsis

Top reasons in the past 6 hours
Sepsis Top Causes: Temperature, Heart Rate

Order | Do Not Order | SUSPECTED SEPSIS STANDING ORDERS

Secure Chat the Physician and Dr. Gabe Wardi

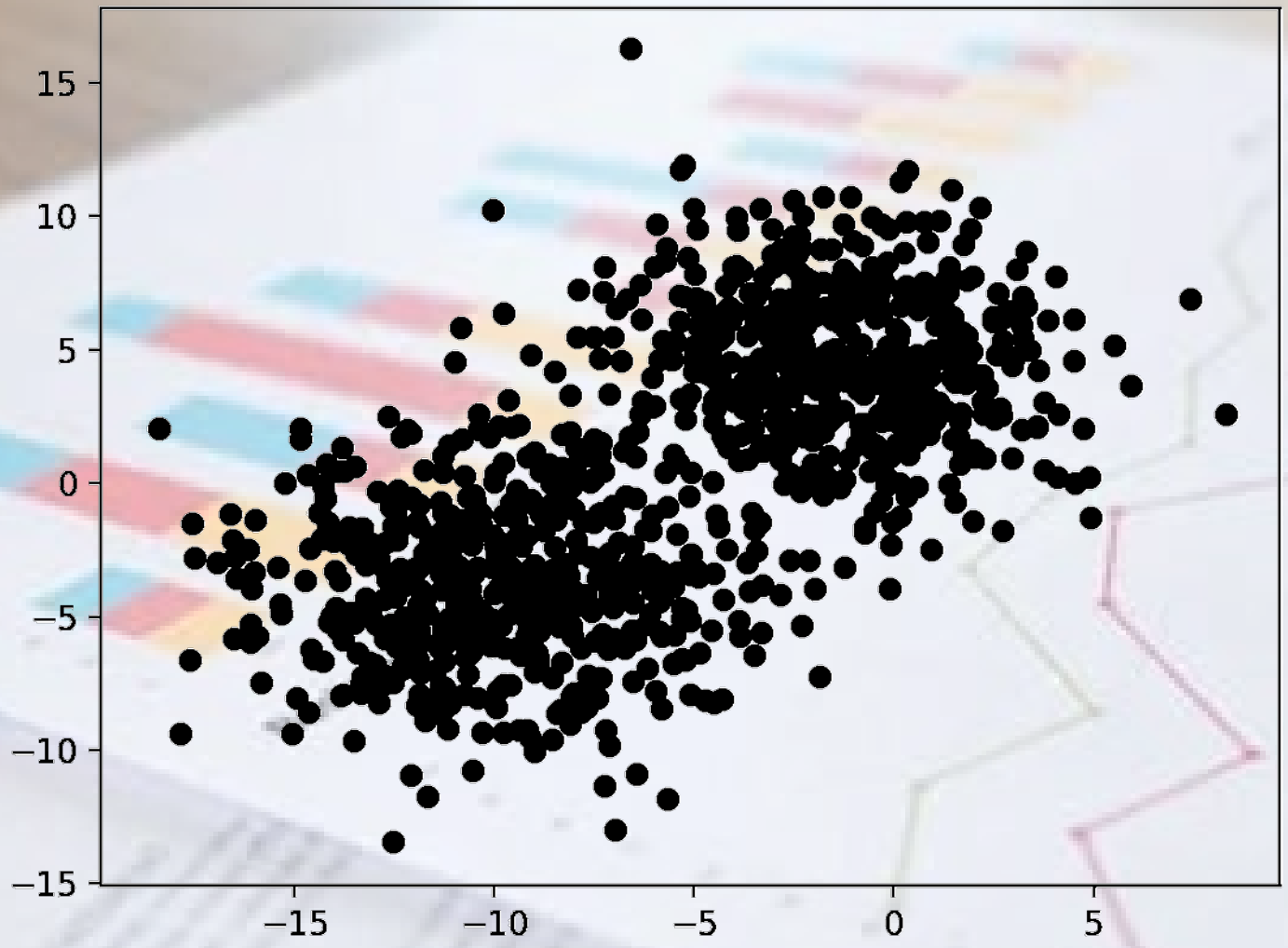
The following actions have been applied:

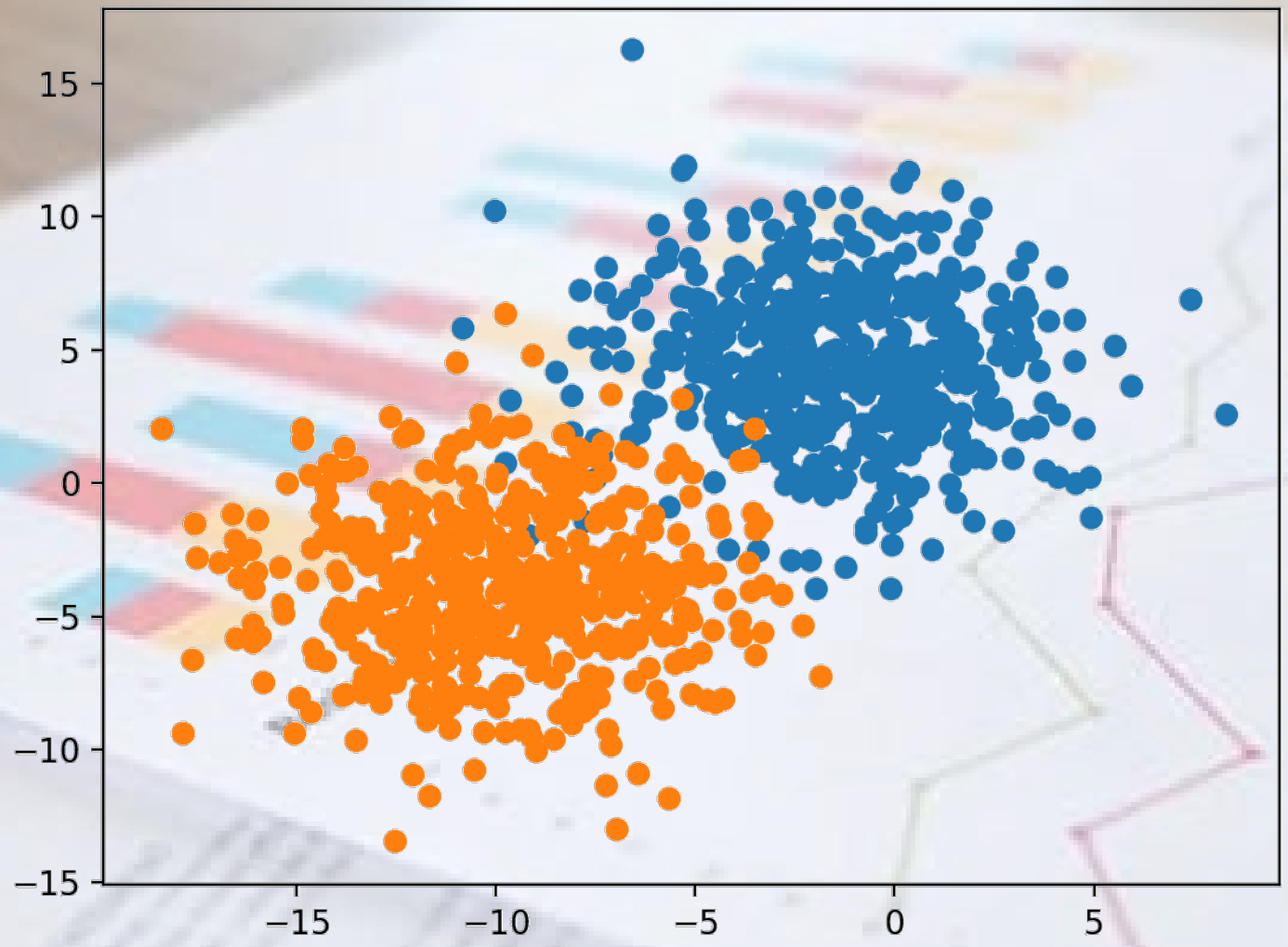
Sent: A summary of this advisory has been sent as a push notification

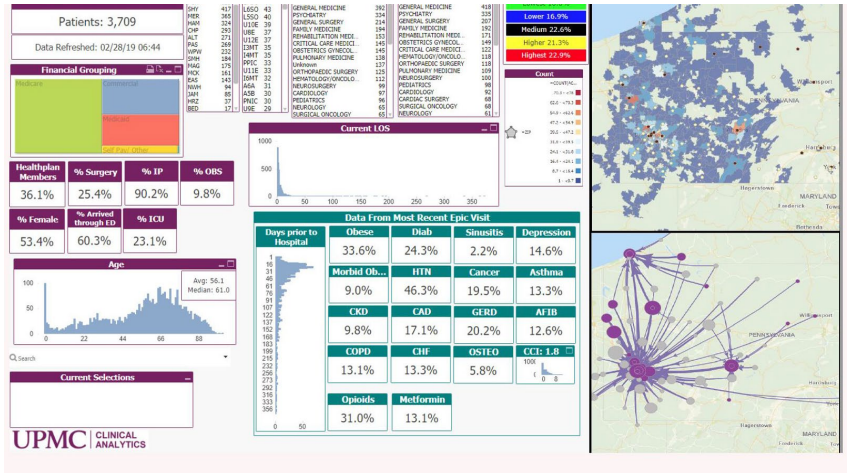
Acknowledge Reason

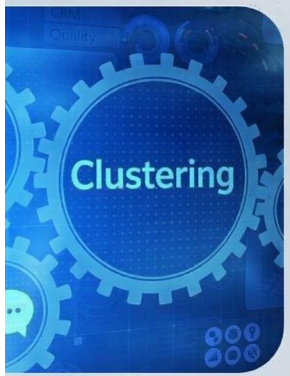
No Infection Suspected | Will Notify MD Immediately | Sepsis Treatment/Workup in Progress

Accept


15
10
5
0
−5
−10
−15
−15
−10
−5
0
5


15
10
5
0
−5
−10
−15
−15
−10
−5
0
5





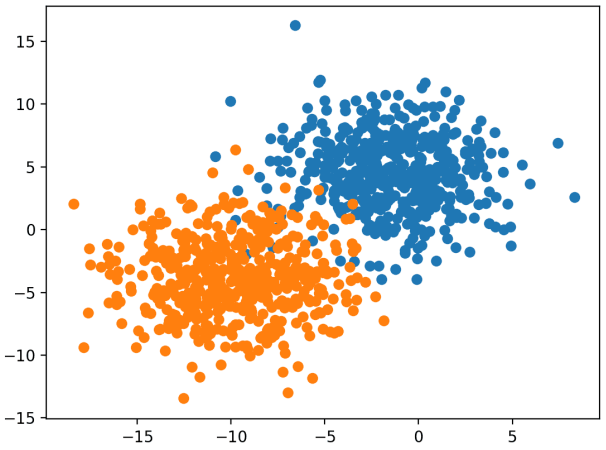
Predictive Analytics

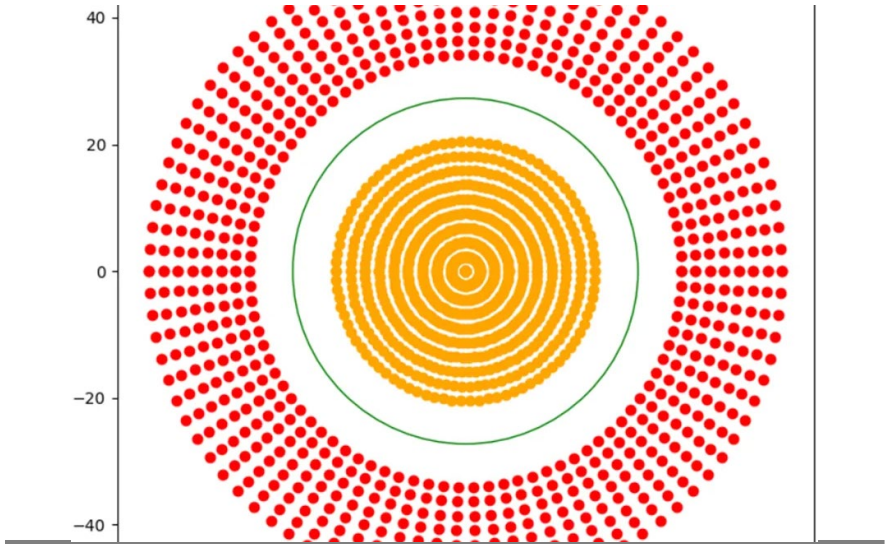
Personalized Care Plans

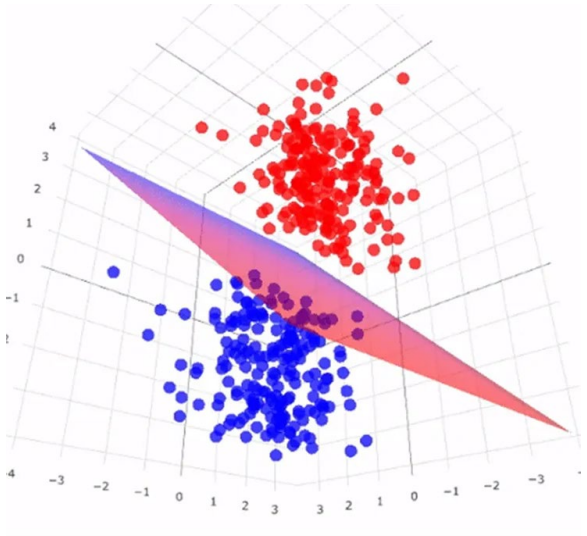
Remote Monitoring

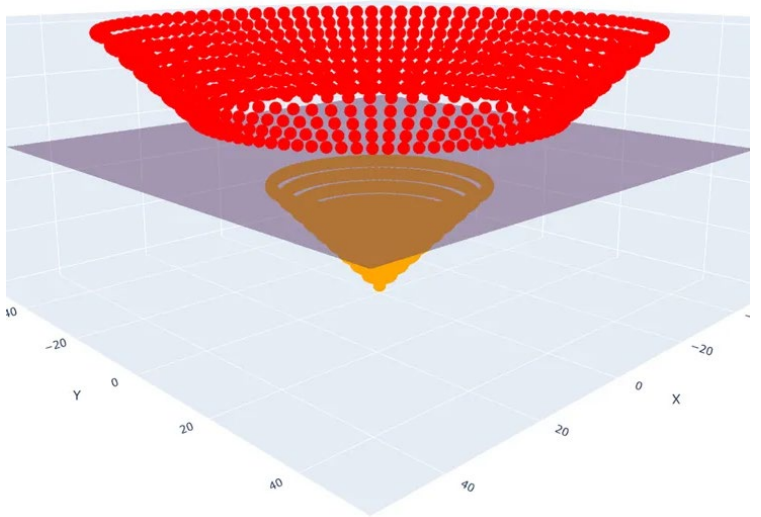
Effective Resource Allocation

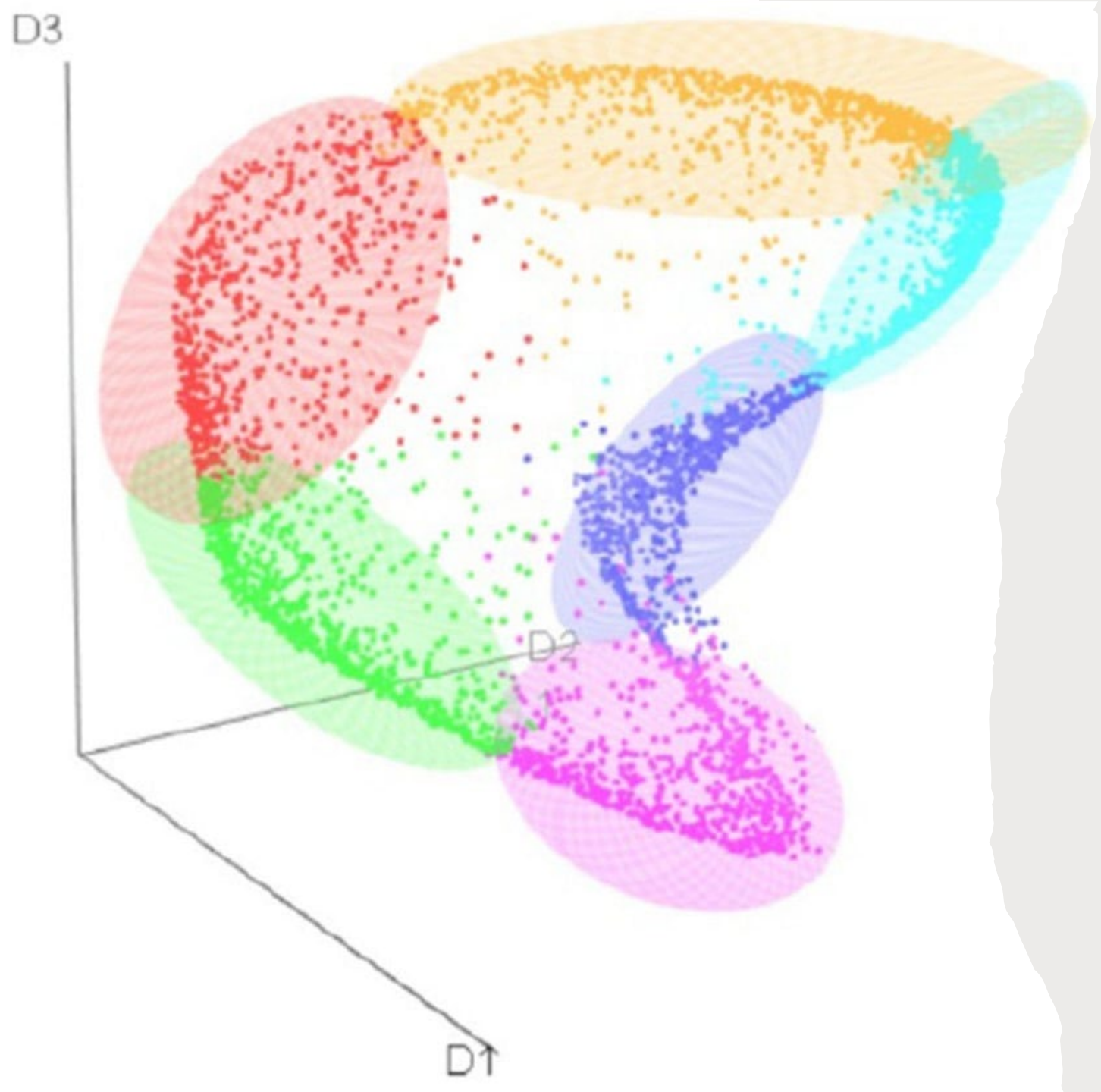
How is AI helpful in reducing readmission in hospitals?


15
10
5
0
−5
−10
−15
−15
−10
−5
0
5

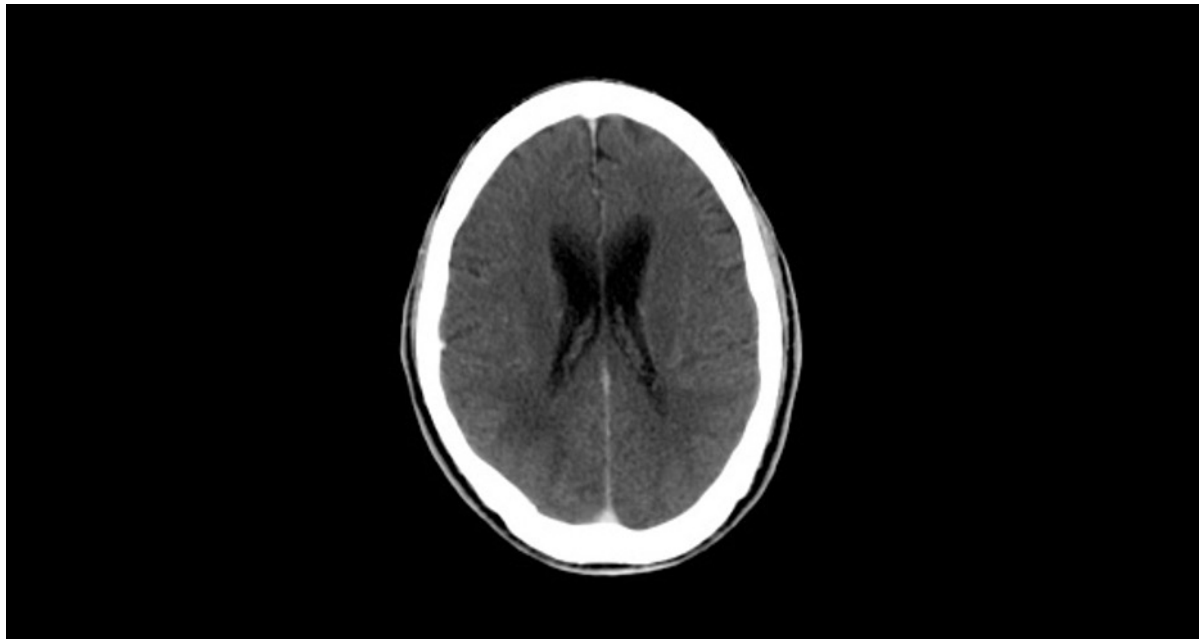

40
20
0
−20
−40

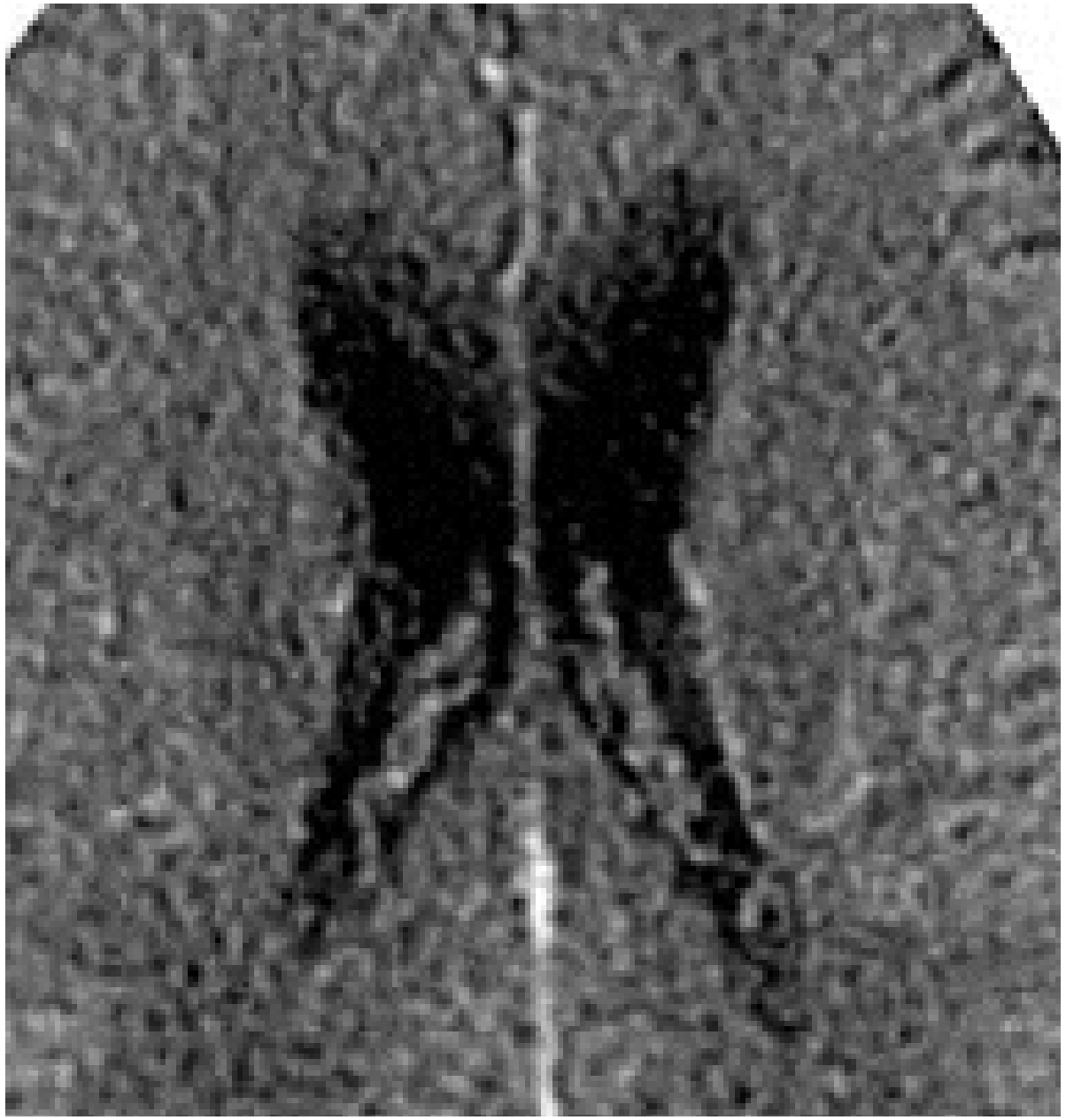


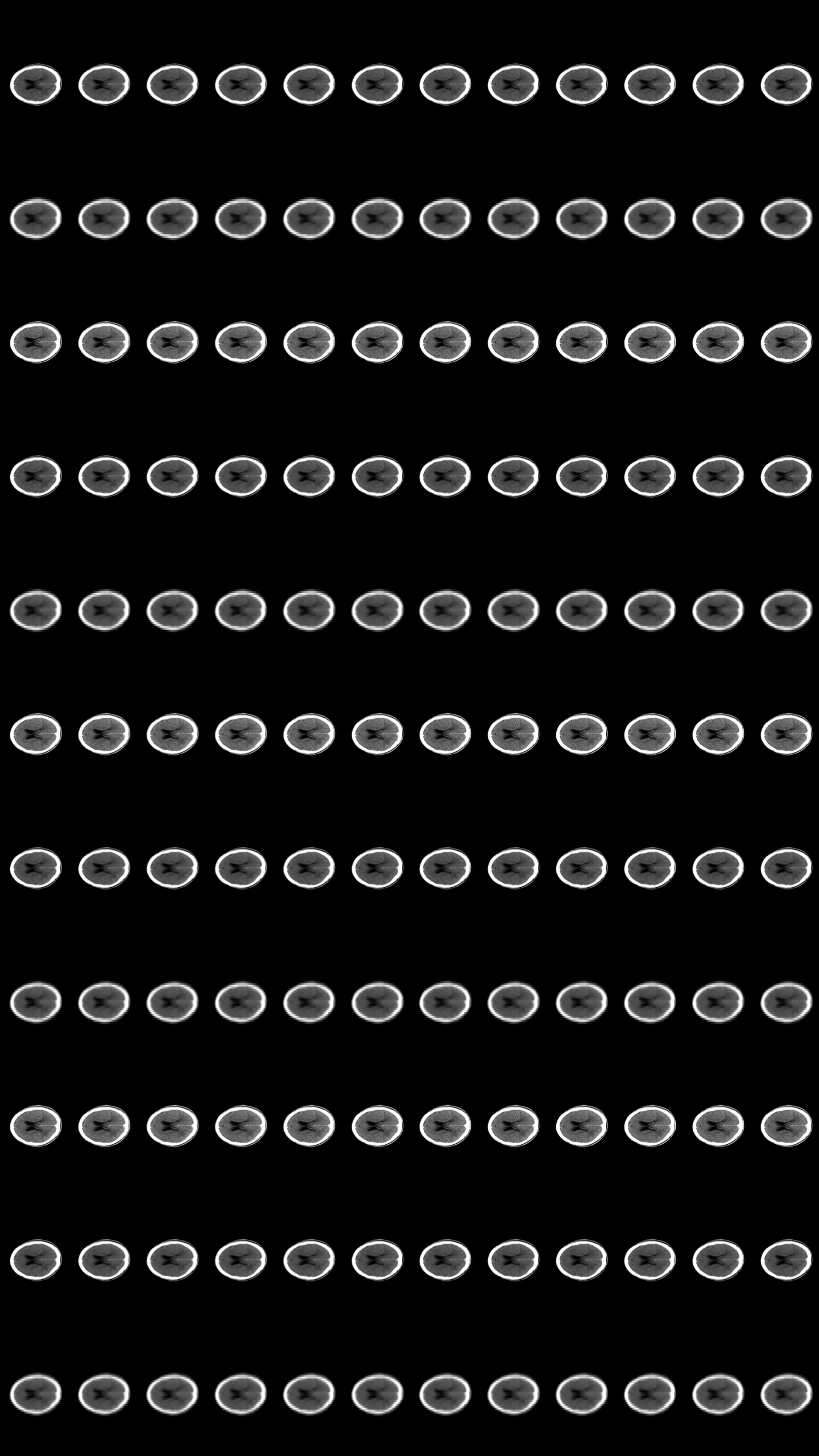

Y
X

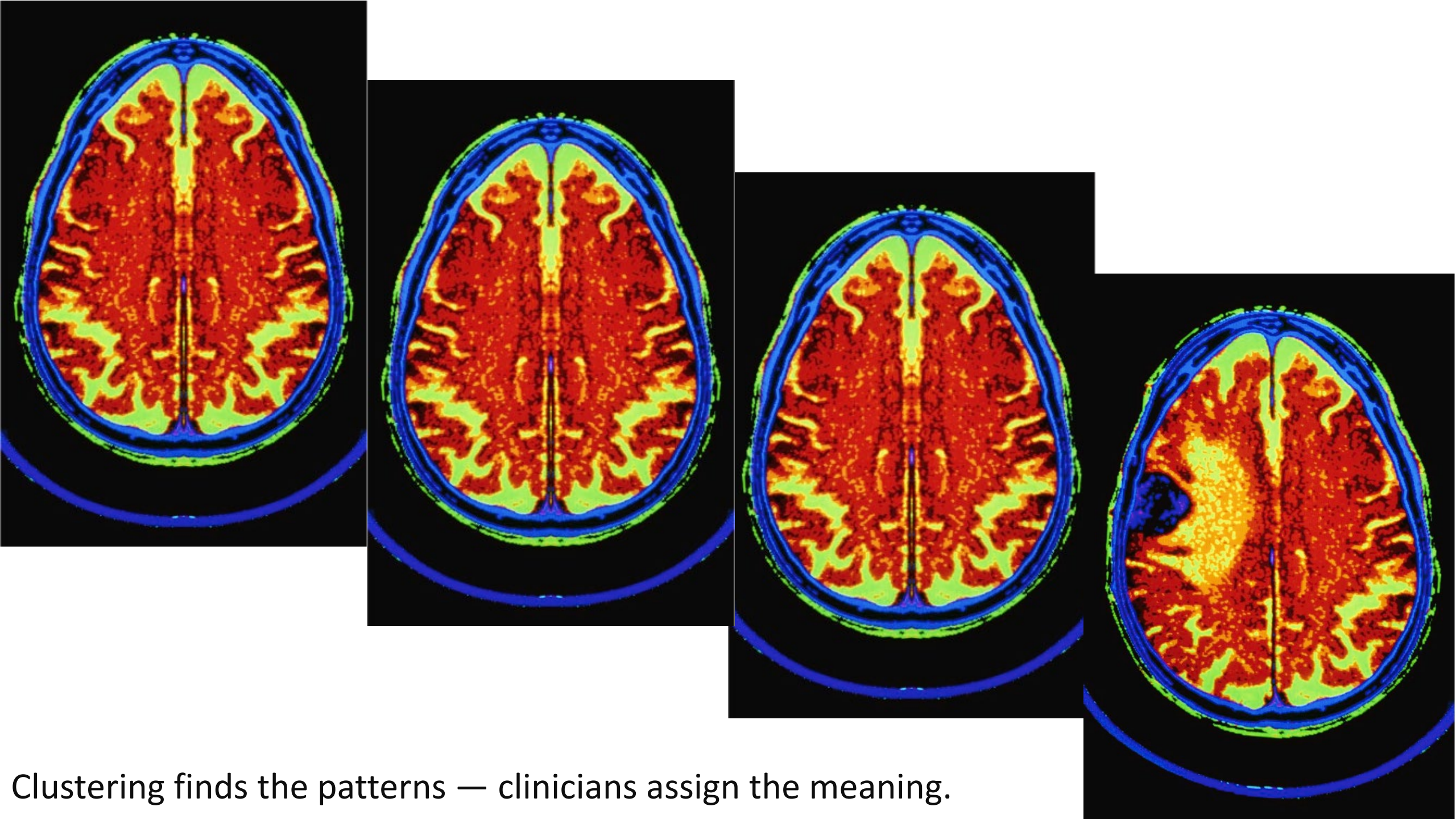


Structure emerges from data





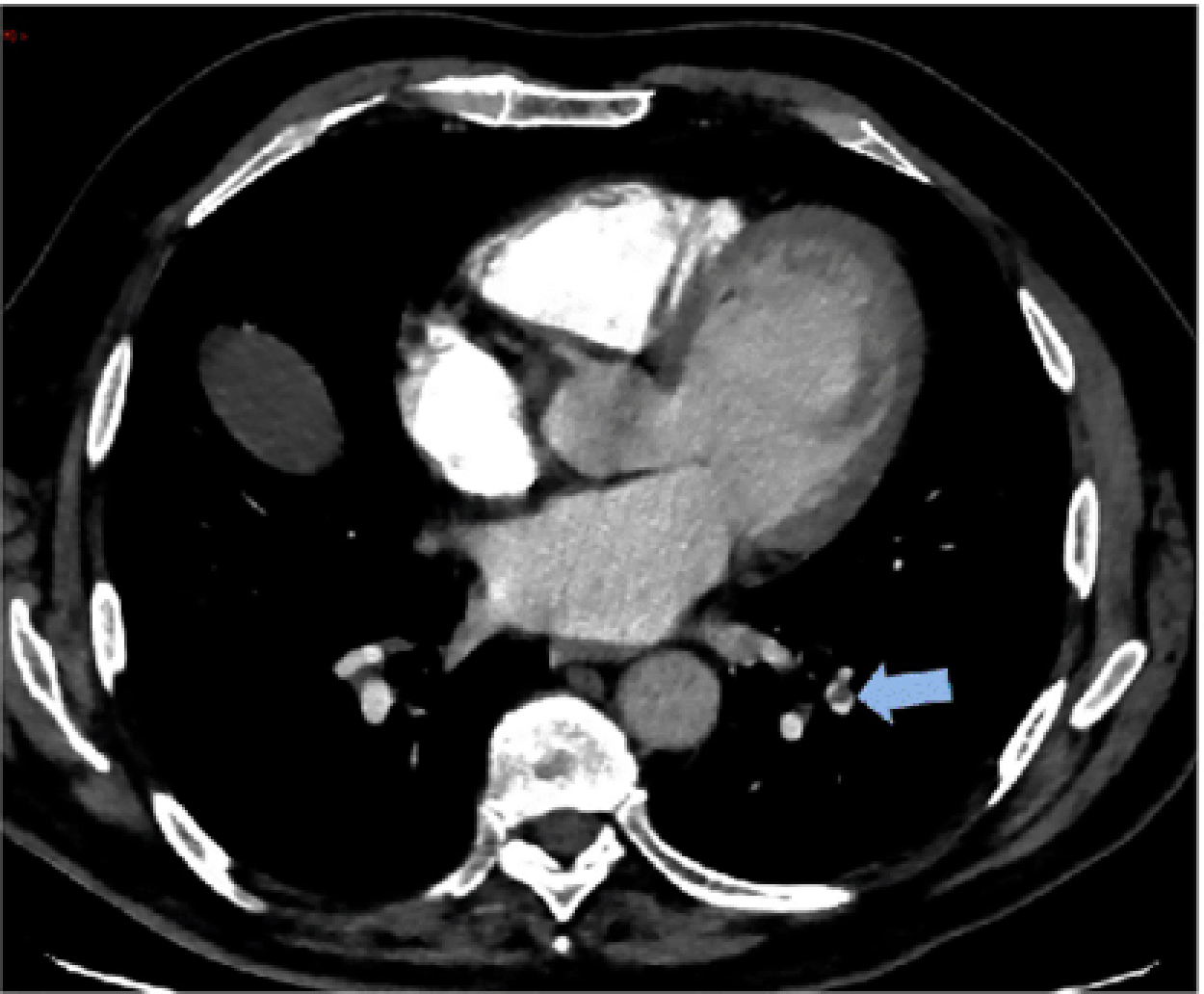




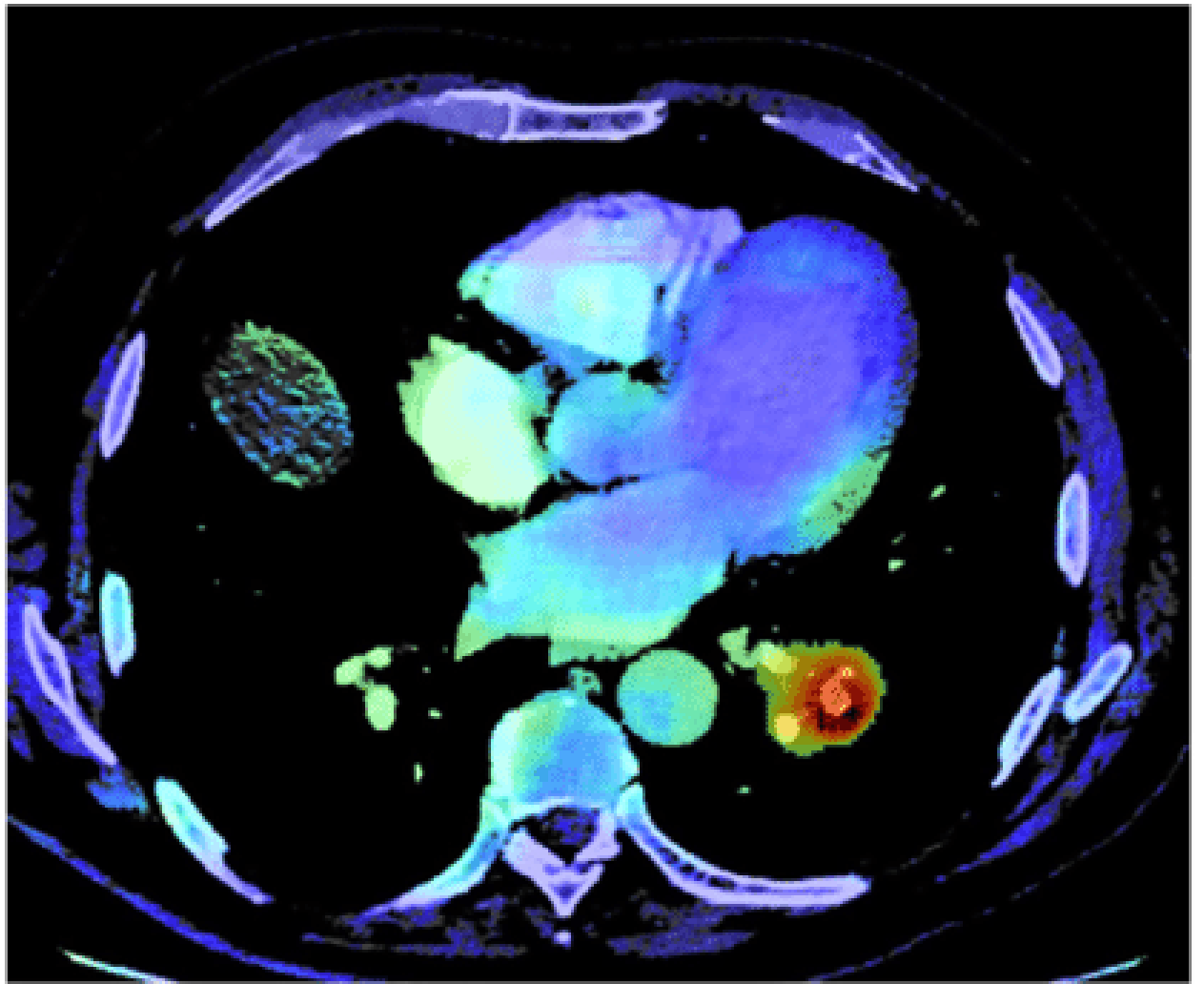
Clustering finds the patterns — clinicians assign the meaning.

aidoc
Always On AI

A

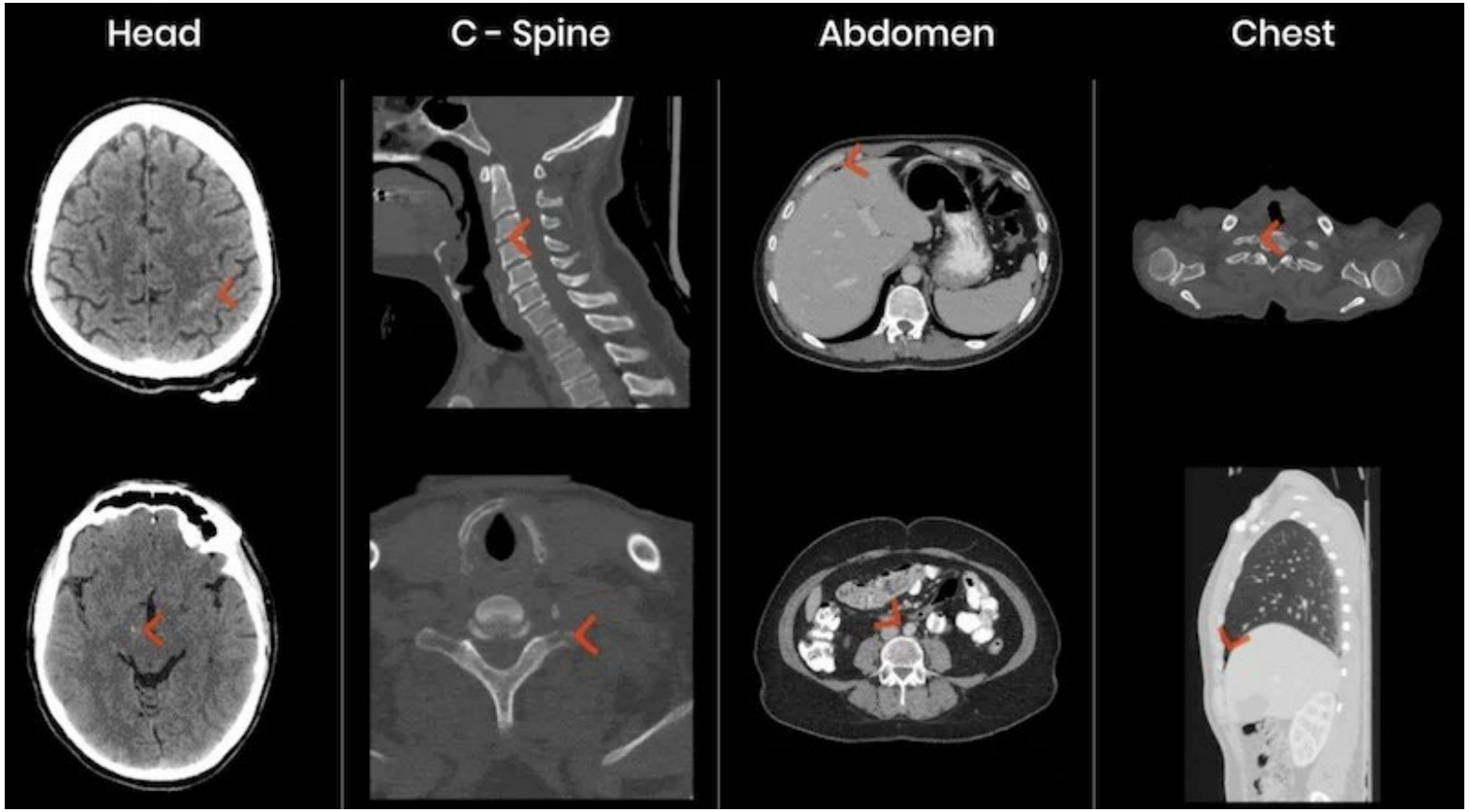


B



Aidoc

- Image Analysis
- Automated Triage & Prioritization
- Seamless PACS & RIS Integration
- Clinical Workflow Activation



From Clusters to Decisions

Uncovering Patient Groups

Clustering techniques reveal hidden groups in radiology data, defining structural patterns to support analysis.

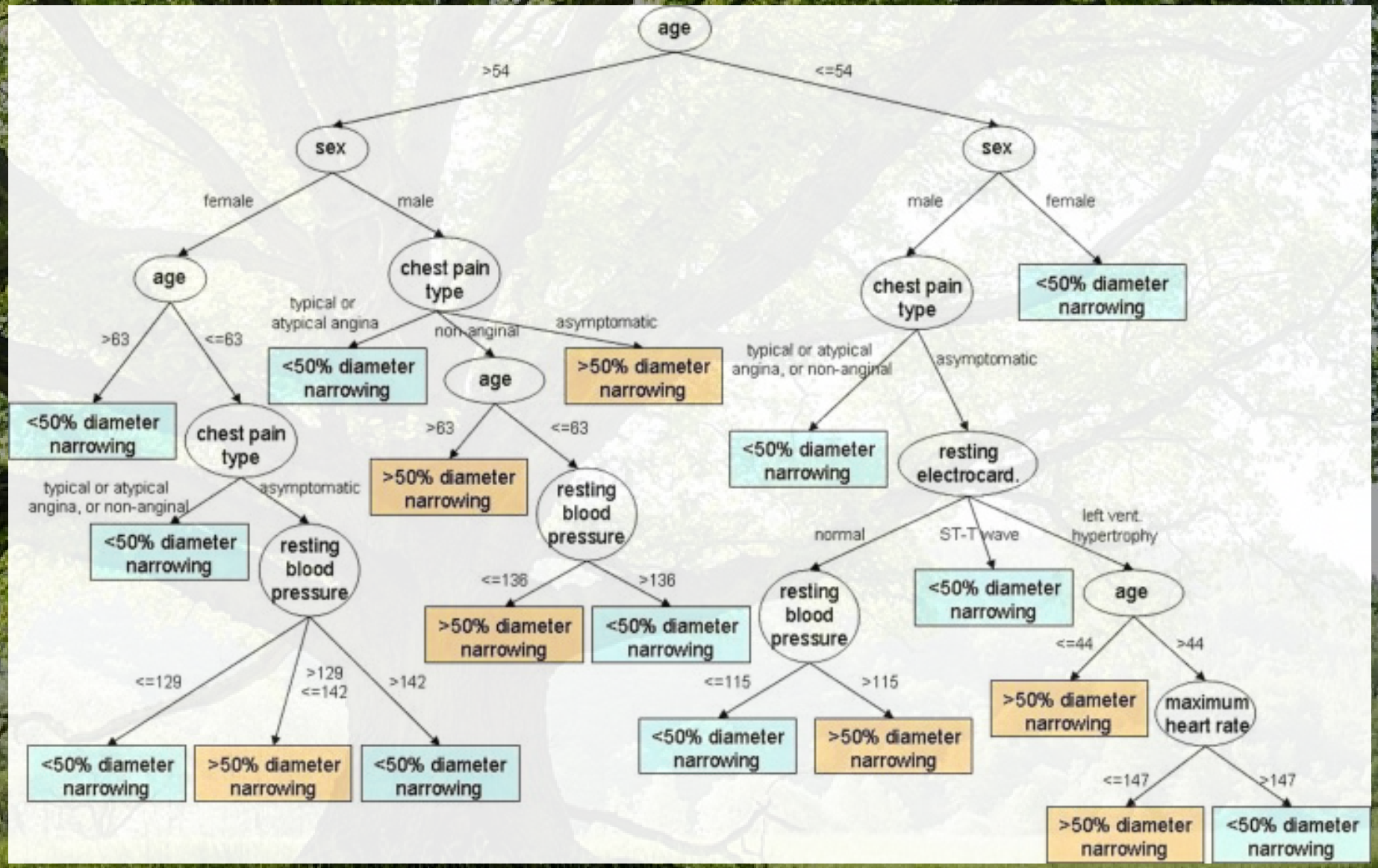
Assigning Patients with Random Forest

Random Forest models assign new patients to identified groups, operationalizing clinical insights for diagnosis.

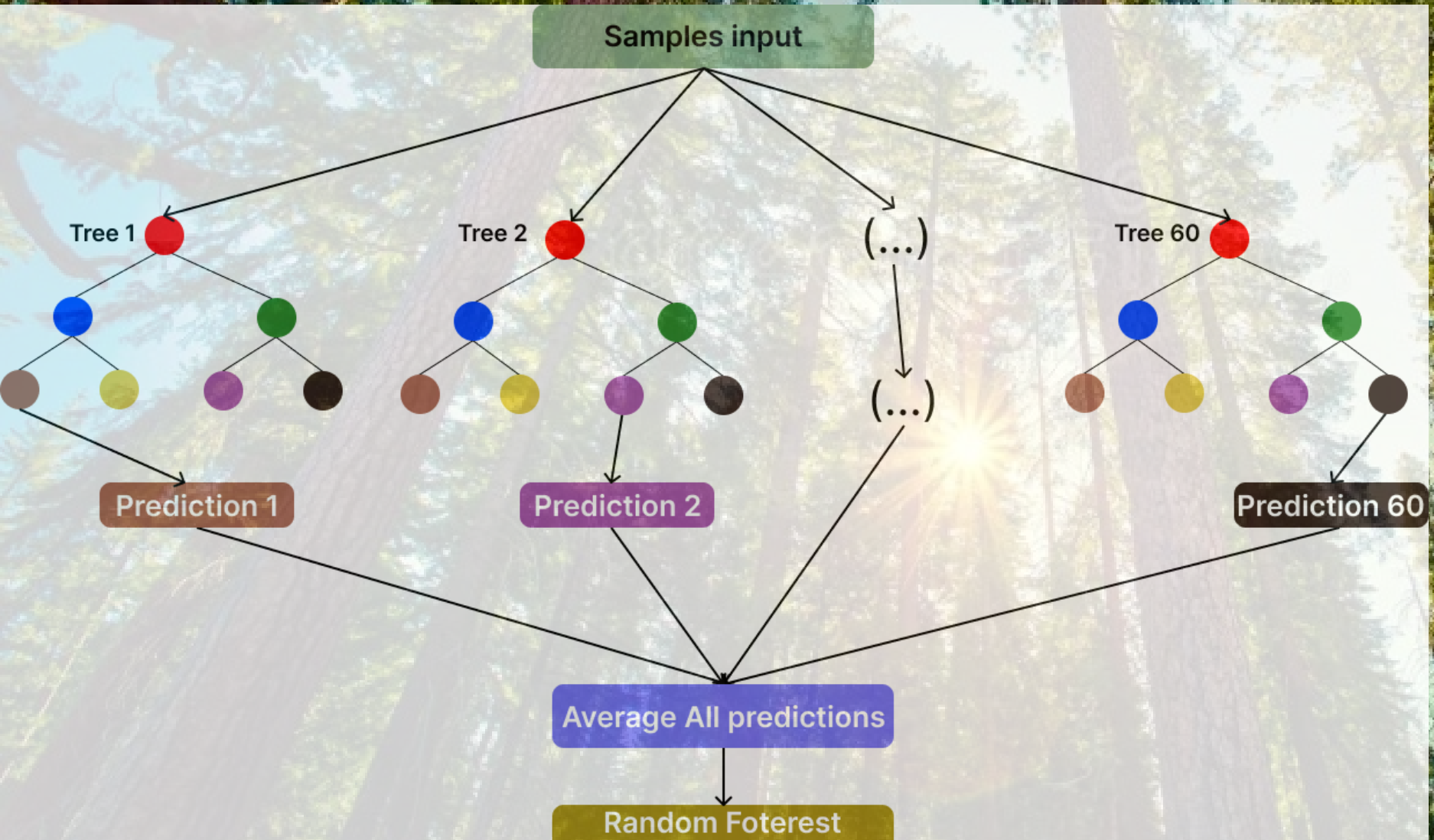
Streamlining Clinical Decisions

This method bridges structural data discovery with actionable clinical decision-making, enhancing diagnostic workflow.

Decision Tree



Random Forest

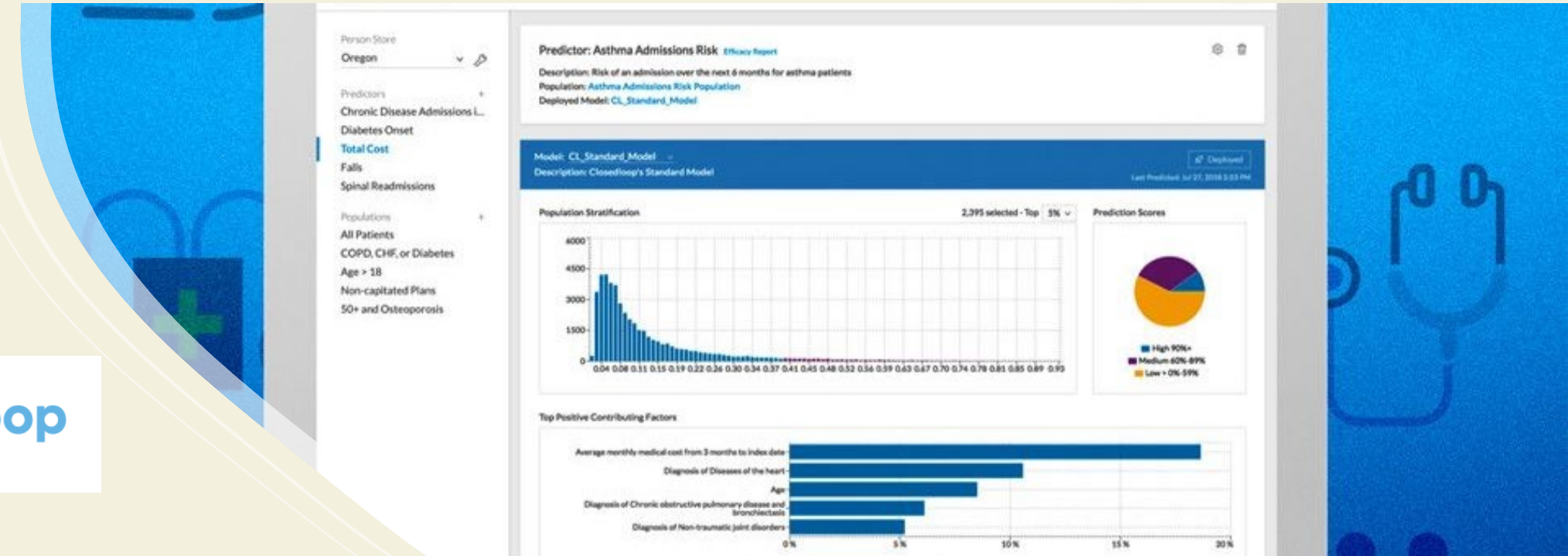


CLOSEDLOOP PREDICT

We predict the future, so you can change it.

Treatments, diagnoses, and interventions are more effective when you find individuals in need before they experience adverse health events. To deliver precise and proactive healthcare with the greatest impact, you need a better way to know what care people need and those who need it the most.

Learn more

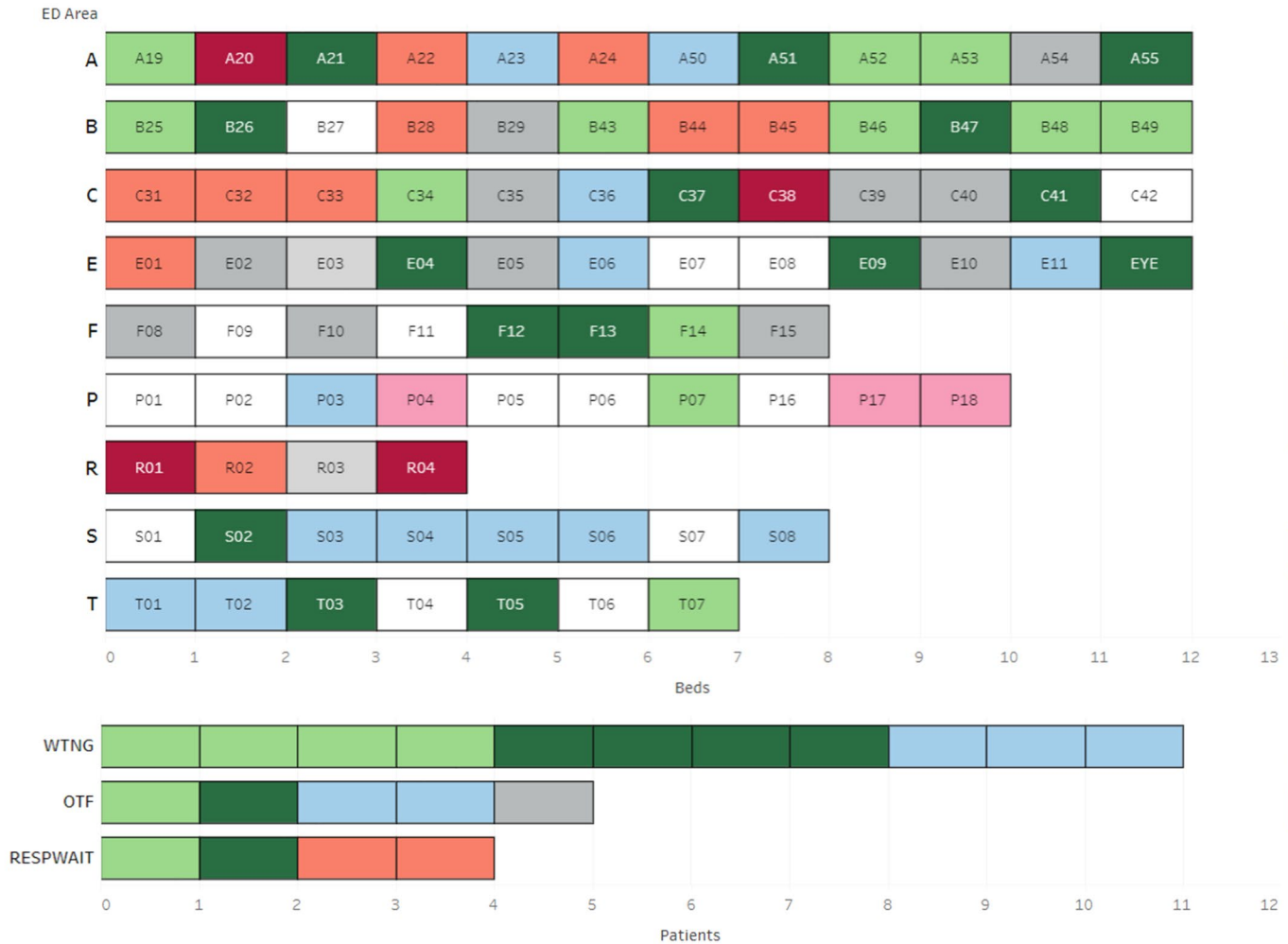


ClosedLoop

Presented Likelihood of ED Patient Admission by Bed

ED Bed View of Intermediate/Stepdown Admission Likelihood

Displays bed and status of patient last documented in the bed.
Last documented move into a bed: 6/18/2020 3:16:00 PM



ED Triage Model

Intermediate/Stepdown

Legend

- Very High Likelihood of Admission
- High Likelihood of Admission
- Medium Likelihood of Admission
- Low Likelihood of Admission
- In the ED, without model output
- Awaiting IP Admit (Boarding)
- Bed's latest patient is a current IP Admit
- Bed's latest patient was discharged
- Pediatric

Admission Likelihood

Very High	High	Med.	Low	Total
4	12	18	21	55

ICU Admission Likelihood

Very High	High	Med.	Low	Total
1	1	27	26	55

Bed Placement Table

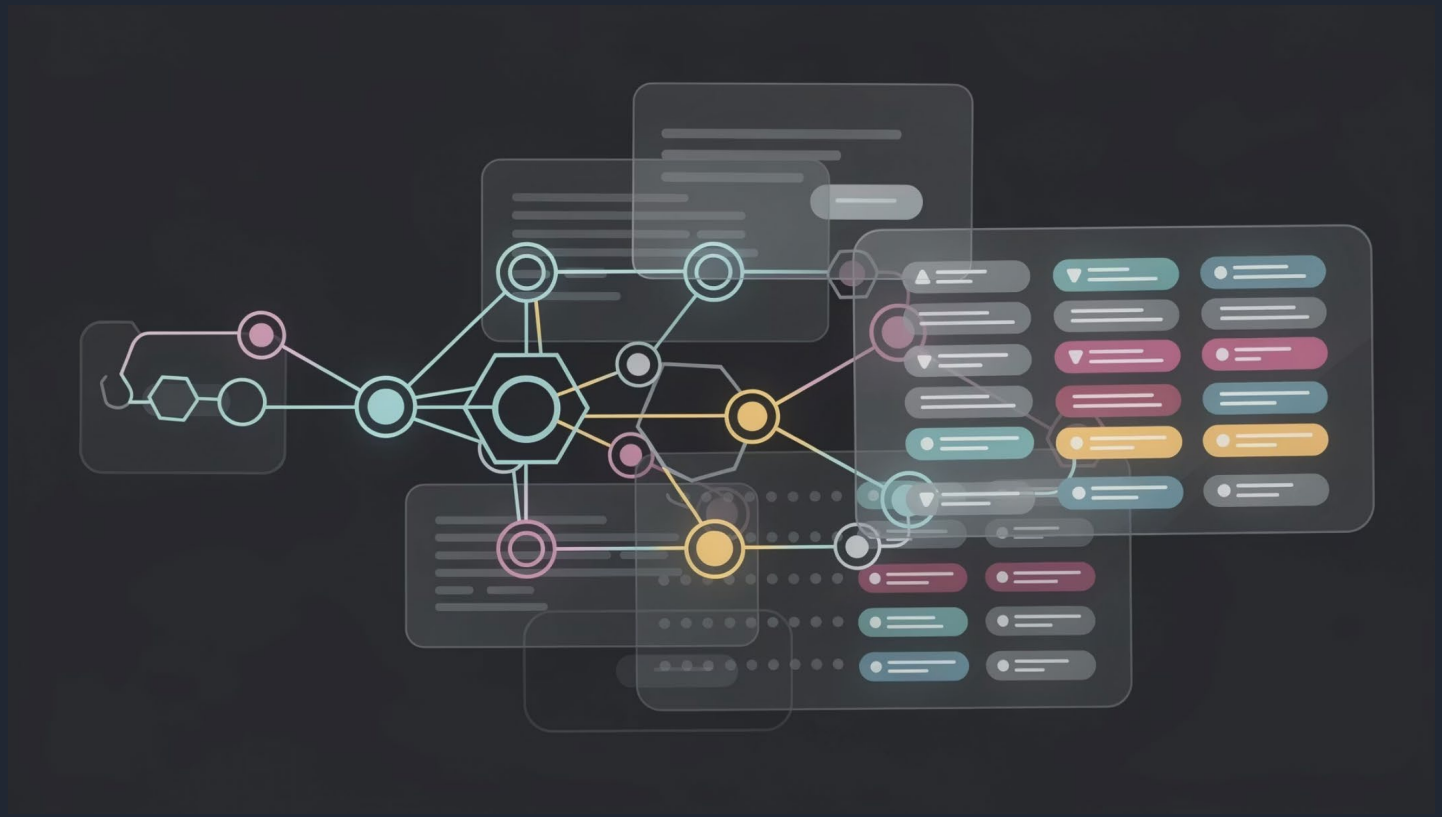
Gen Adm Vol Est		ICU Adm Vol Est	
Low Est	High Est	Low Est	High Est
17	27	1	4


LLM
LARGE LANGUAGE MODELS
AI

What Exactly Is an LLM?

Large Language Model — a type of AI trained on massive amounts of text to understand and generate human language.

How LLMs Actually Work



LLMs are trained to **predict the next word** — over and over, billions of times — until they develop a sophisticated model of language, facts, and reasoning.

Important caveat: LLMs do not "understand" language the way humans do. They are sophisticated pattern matchers.

This distinction has major implications for how we should trust and verify their outputs in clinical settings.

Why Should ED Operational Leaders Care?

Emergency departments operate under relentless pressure — documentation demands alone consume hours of clinician time every shift. LLMs directly address the core friction points that drive burnout and reduce throughput.

Documentation Burden

LLMs can draft notes, summaries, and discharge instructions in seconds.

Throughput Pressure

Faster documentation and decision support translate directly into shorter door-to-disposition times and improved patient flow.

Workflow Efficiency

LLMs act as a force multiplier — enabling every member of the care team to do more with the time they have.

LLMs Are Already Everywhere

Your patients are using them. Your trainees are using them. And increasingly, your hospitals are, too.

100M

ChatGPT Users

Reached 100M in 2 months — fastest product adoption in history

~50%

Physicians Using AI

Report using AI tools in some form in their practice (AMA, 2023)

$45B

Healthcare AI Market

Projected global healthcare AI market by 2026

What LLMs Do Well

Summarization

Condense lengthy charts or research articles into concise, actionable summaries .

Documentation Drafting

Generate clinical notes, leaving the clinician to review and refine rather than write from scratch.

Patient Communication

Produce plain-language discharge instructions tailored to the patient's condition and reading level.

Where LLMs Fall Short

Hallucinations

LLMs can generate confidently stated, completely fabricated information — including fake citations, incorrect dosages, and non-existent guidelines.

No True Reasoning

They cannot logically deduce or perform multi-step clinical reasoning. Pattern matching is not the same as analytical thought.

Training Data Bias

Models reflect the biases present in their training data, including racial, gender, and socioeconomic disparities embedded in historical medical literature.

Not a Clinical Replacement

LLMs cannot examine a patient, integrate real-time vitals, or exercise the judgment that comes from years of clinical training and experience.

Ambient Scribes

Abridge and similar ambient documentation platforms represent one of the most impactful LLM applications in clinical medicine today.

1. **Reduces Documentation Time**

   Studies show up to 70% reduction in time spent on after-visit notes

2. **Improves Patient Engagement**

   Clinicians maintain eye contact and focus on the patient, not the screen

3. **Structured Output**

   Generates note sections aligned to standard clinical templates

ChatGPT in Healthcare

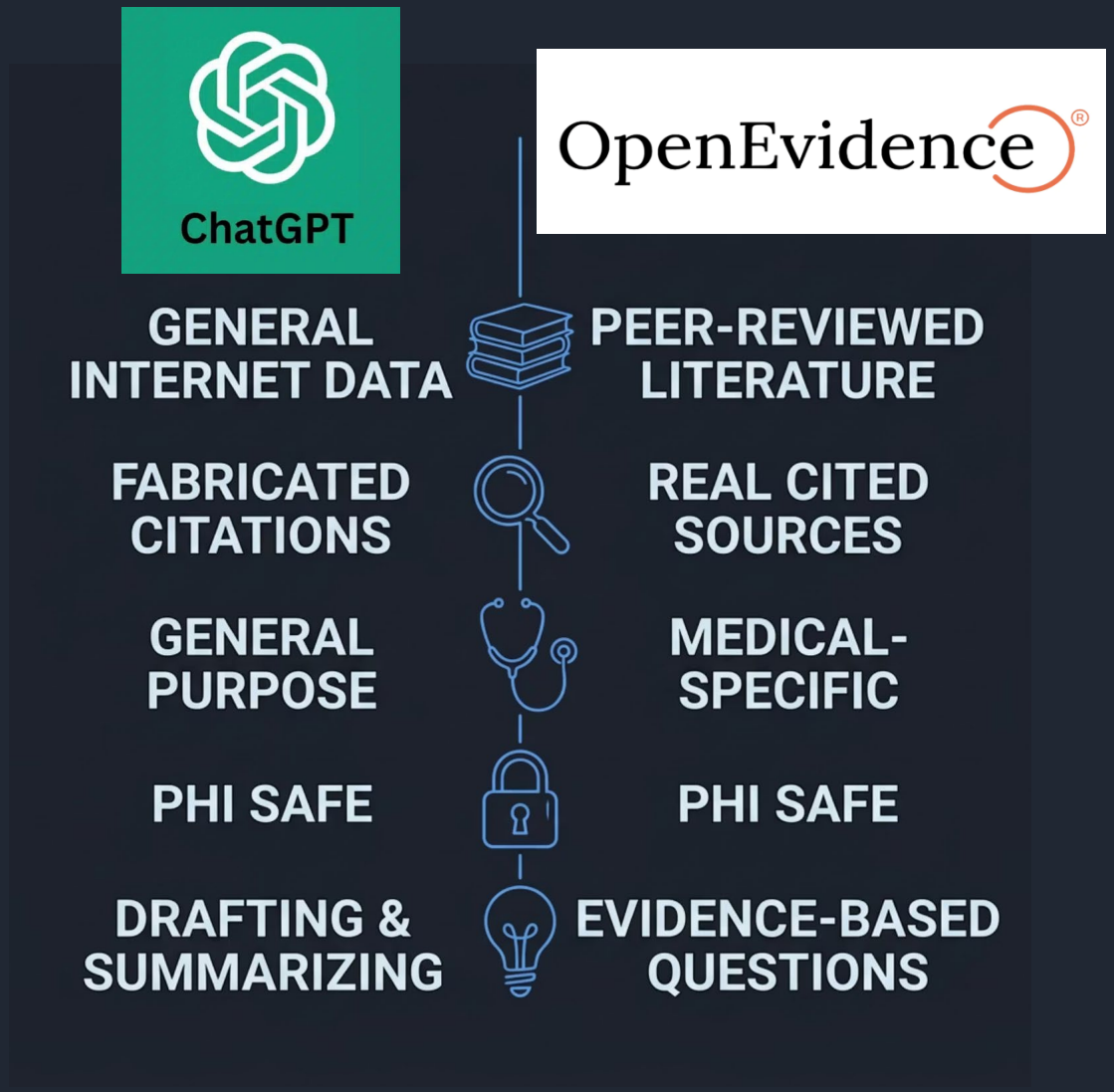
What It Does Well

ChatGPT excels as a **cognitive assistant** — helping clinicians draft patient education materials, summarize literature, brainstorm differential diagnoses, and structure complex communications. Its breadth of knowledge and conversational interface make it highly accessible.

What to Watch Out For

- **HIPAA compliance:** The standard ChatGPT interface is NOT HIPAA-compliant. Enterprise versions with BAAs exist but require institutional procurement.
- **Verification is mandatory:** Always confirm factual claims, drug doses, and cited sources independently before clinical use.

A Better Option for Clinical Questions



Open Evidence is a medical-specific LLM trained exclusively on peer-reviewed literature — think PubMed meets ChatGPT, with real citations you can verify.

- Grounded in actual studies — reduces hallucination risk
- Free to use for clinicians
- Ideal for point-of-care evidence questions
- Still requires clinical judgment to interpret

AskEMDI

Turning emergency medicine data into actionable intelligence

The American College of Emergency Physicians (ACEP) Emergency Medicine Data Institute (EMDI) is leading a new era of care based on Real World Data (RWD). EMDI's Clinical Emergency Data Registry (CEDR) includes data collected from over 170 million emergency encounters – the nation's largest emergency medicine data resource.

AskEMDI was created by ACEP and its partners to provide authorized users with intuitive access to cleansed, standardized, and de-identified data derived from CEDR without requiring specialized technical knowledge. AskEMDI uses a conversational, chatbot-style user interface and artificial intelligence to translate natural language questions into CEDR queries. AskEMDI is intended for authorized users as an easy to use tool to support quality initiatives and clinical research.

EM-Tuned Knowledge

Trained on ACEP guidelines, EM literature, and clinical protocols — answers reflect real emergency practice

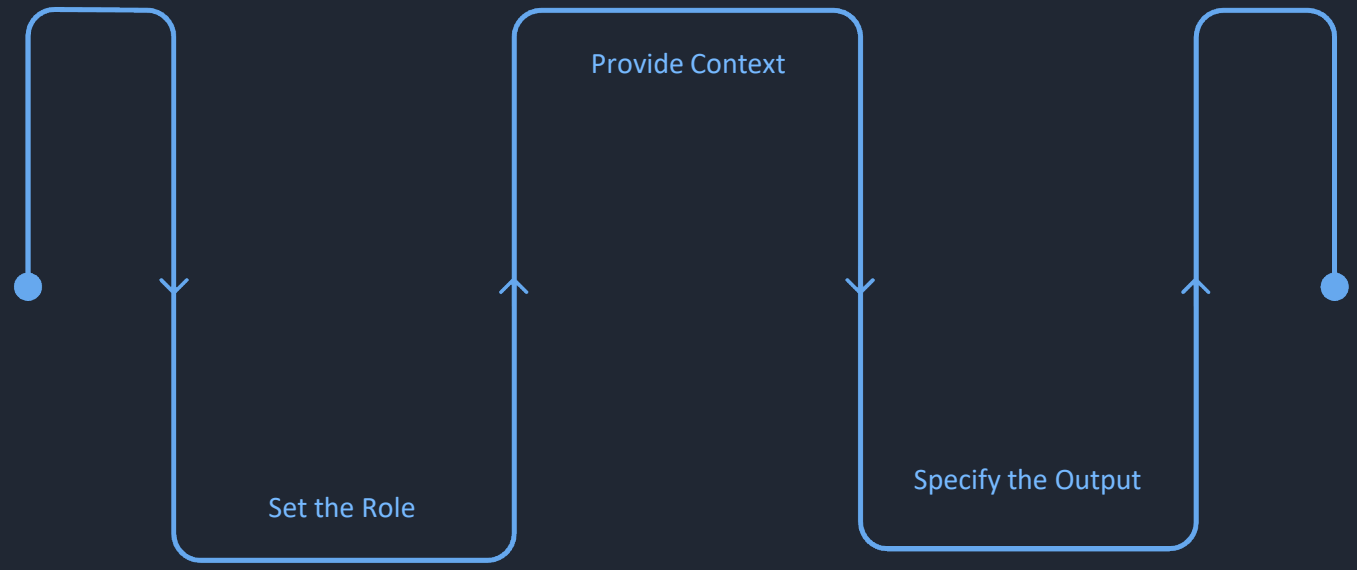
Evidence-Referenced

Responses include sourced references to reduce reliance on unverified outputs

Purpose-Built

More precise for EM queries than general-purpose tools — reduces other specialty answers

Prompt Engineering: Ask Better, Get Better



✅ Pearls

- Assign a role: "You are a board-certified EM physician…"
- Be specific about format and length
- Iterate — ask follow-ups to refine

⚠️ Pitfalls

- Vague prompts yield vague answers
- Never input PHI in consumer tools
- Always verify clinical output
- Sycophancy (agreement bias)

The quality of AI output is directly proportional to the quality of your prompt. A little structure goes a long way.

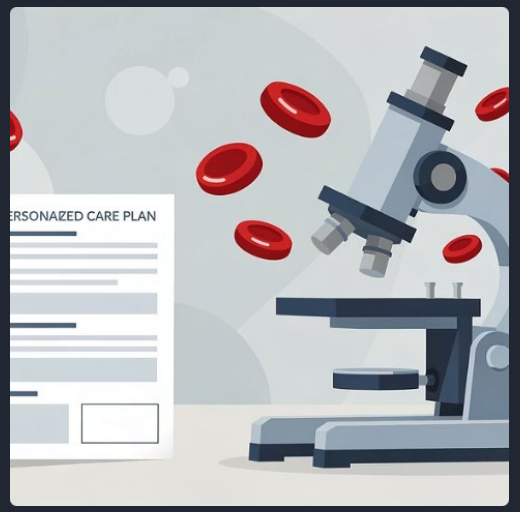
LLM Use Cases in the Duke ED

Scout

A prompt-based Epic chart search tool that allows clinicians to query patient records in plain language —reducing the time needed to extract relevant history from complex charts.

Rusty

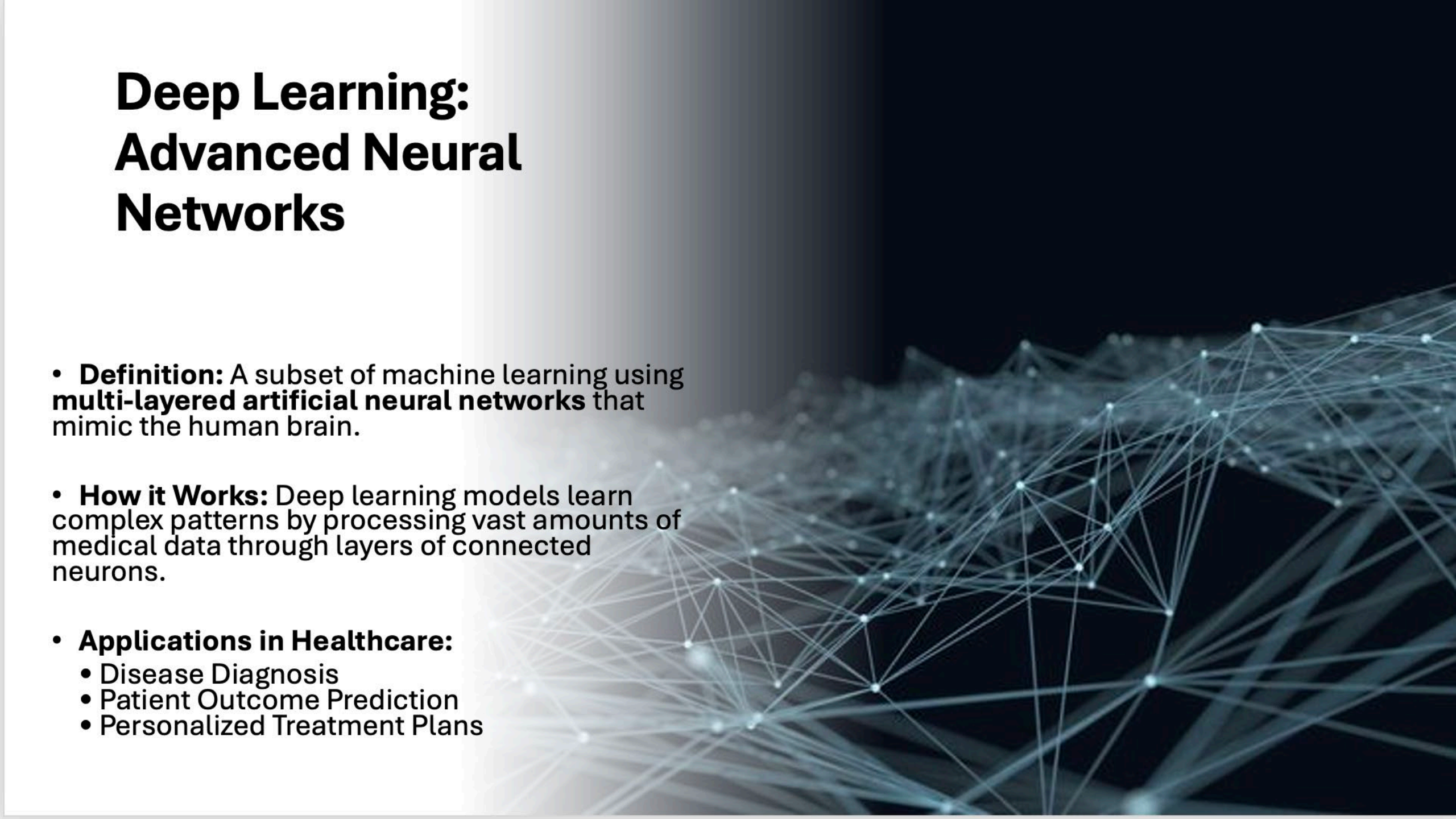
A prompt-based search tool that allows clinicians to query the ED CEU protocols for clinical guidance.



Sickle Cell Tool

A tool that generates individualized management plans for patients with sickle cell disease based on their history, prior treatments, current presentation, and existing literature.

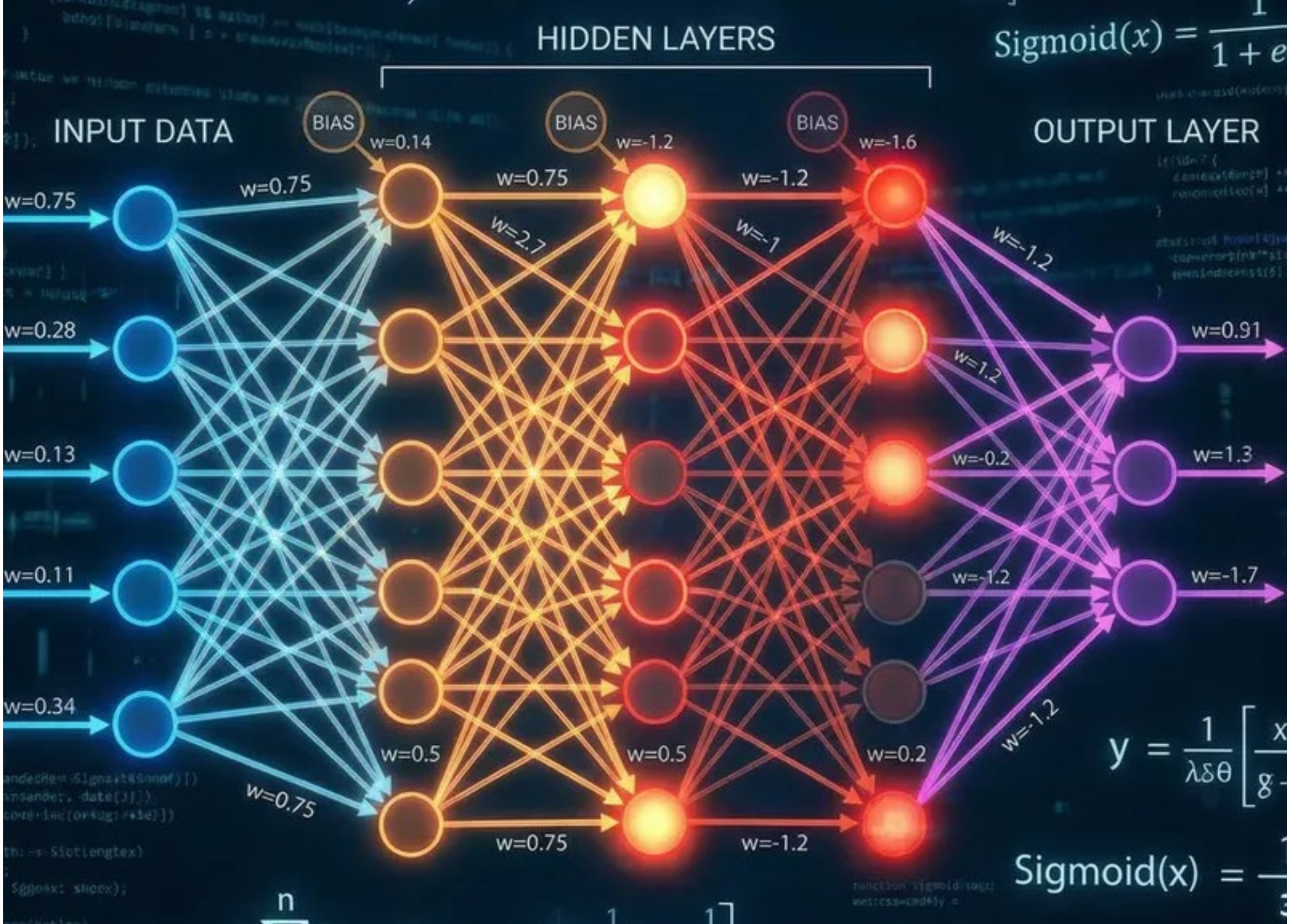
Deep Learning: Advanced Neural Networks



- **Definition:** A subset of machine learning using **multi-layered artificial neural networks** that mimic the human brain.

- **How it Works:** Deep learning models learn complex patterns by processing vast amounts of medical data through layers of connected neurons.

- **Applications in Healthcare:**
  - Disease Diagnosis
  - Patient Outcome Prediction
  - Personalized Treatment Plans


HIDDEN LAYERS
INPUT DATA
OUTPUT LAYER
BIAS
BIAS
BIAS
w=0.14
w=-1.2
w=-1.6
w=0.75
w=0.28
w=0.13
w=0.11
w=0.34
w=0.75
w=0.75
w=2.7
w=-1.2
w=-1
w=-1.2
w=1.2
w=-0.2
w=-1.2
w=-1.2
w=0.91
w=1.3
w=-1.7
w=0.5
w=0.5
w=0.2
w=0.75
w=0.75
w=-1.2
Sigmoid(x) =
y =
Sigmoid(x) =

SEPSIS WATCH +

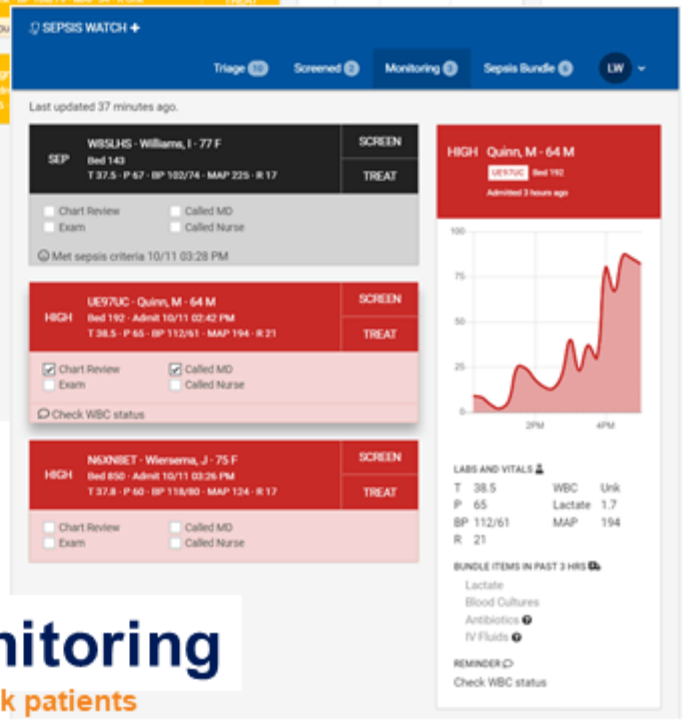
Think beyond detection

Triage

New patients with risk of sepsis

Screened

Low and medium risk patients

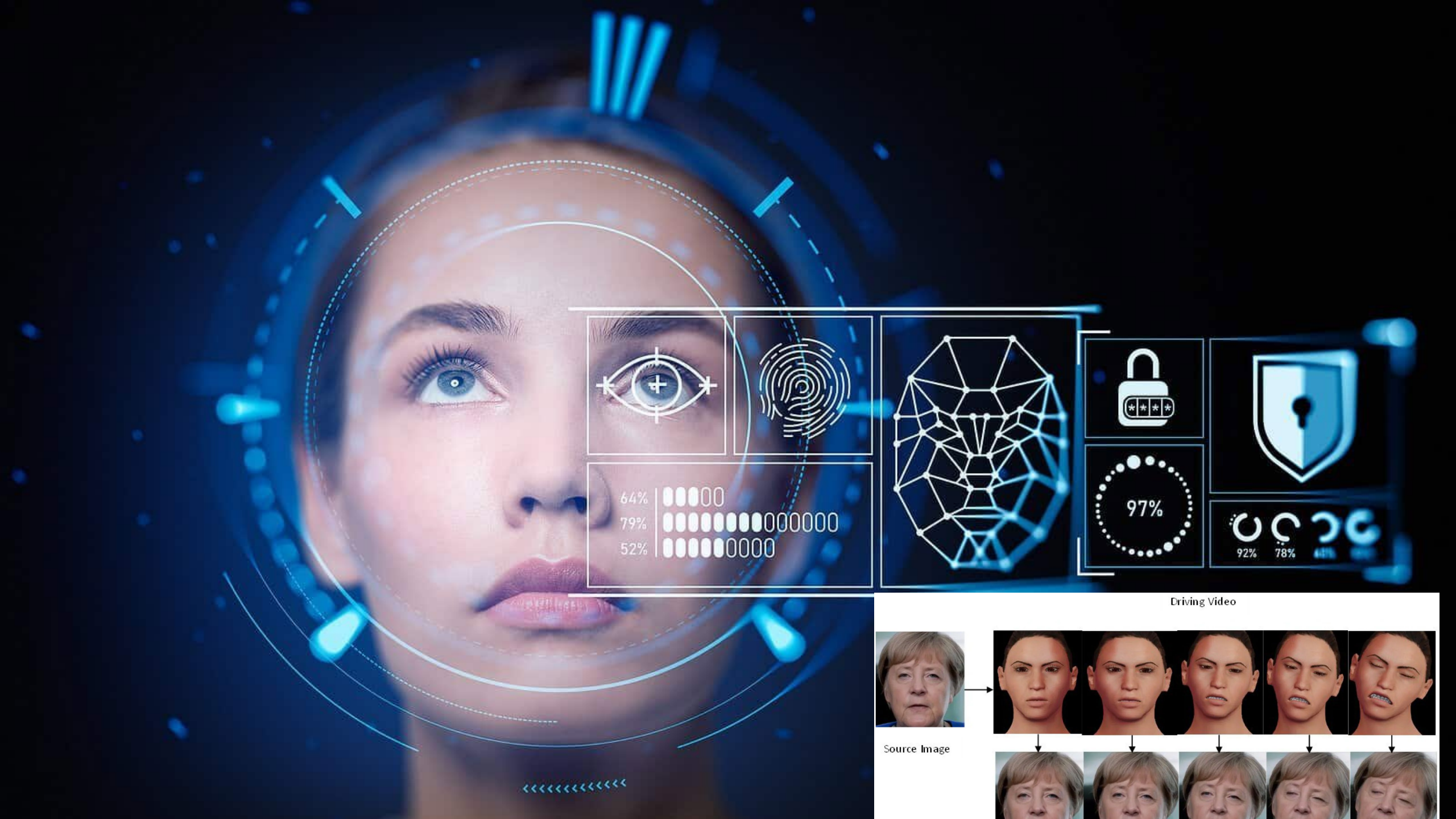


Monitoring

High risk patients

- With the use of regression and random forest Sepsis Watch used millions of data points over hundreds of thousands of patient encounters to develop a classification model for patients at risk for sepsis.

- Unlike many other models Sepsis Watch does not wait for clinical data to meet SEP bundle criteria before identification of patients.


64%
79%
52%
97%
92%
78%
Driving Video
Source Image

Video

High-quality, two-way video with multiple participants for virtual care.

Audio

High-quality, two-way audio and voice-activated services for real-time assistance.

Location

Ultra-Wideband Technology (UWB) tracks the movement and flow of assets throughout the hospital.

Integrations

Complete interoperability for your current and future technologies.

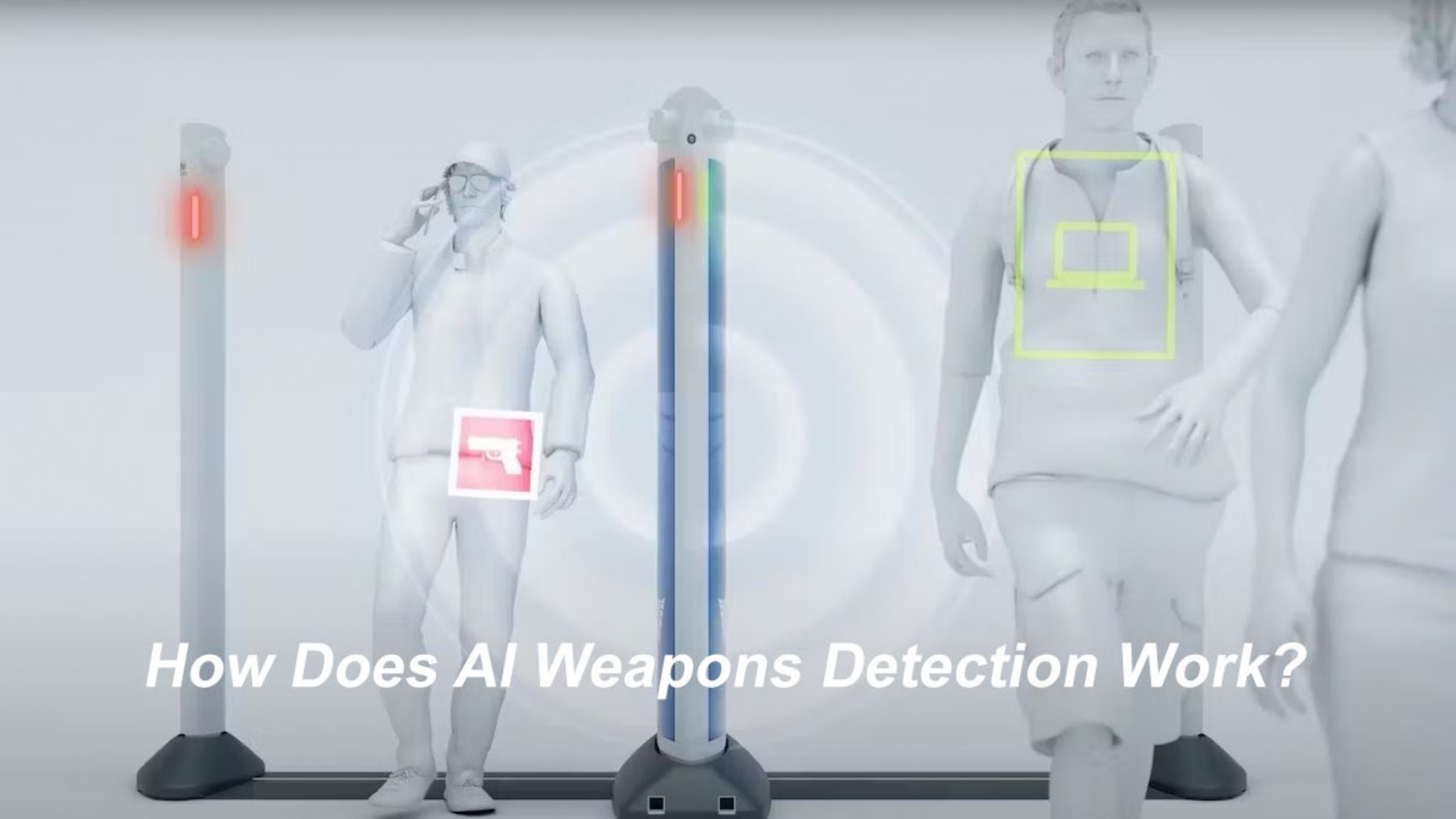
The patient room is equipped with AI-powered devices that support documentation and remove administrative burdens so clinicians can keep their eyes on patients and deliver truly personalized, human-centered care.

Remote nurses and observers monitor patient room activity off-site and interact virtually with patients and clinicians.

Patient Room

Operating Room

Clinic


How Does AI Weapons Detection Work?

From Tools to Leadership

Now that we discussed *what* AI can do — let's talk about *what it means* for you as an ED operations leader.

Social Potpourri

Big Picture AI Topics Every ED Leader Should Know

Ethics

Fairness, transparency, and patient autonomy in AI-assisted care

Risk

Patient safety, error accountability, and quality oversight

Legal

Liability, malpractice, FDA regulation, and informed consent

Privacy

HIPAA in the age of AI

Ethical Considerations

Bias and Disparities

AI models trained on historically biased medical data may perpetuate or amplify disparities in care.

Transparency Challenges

Many LLMs are "black boxes" — their reasoning is not interpretable. Clinicians cannot always understand why an AI produced a given recommendation.

Patient Trust

Patients have a right to know when AI is involved in their care. Informed consent frameworks are still evolving.

Data Privacy

LLM platforms that store or process patient data must meet HIPAA and institutional data governance standards. Vendor agreements require careful legal review.

Risk & Patient Safety

Where Things Can Go Wrong

Alert Fatigue

AI-generated recommendations can overwhelm clinicians the same way CDS alerts do — automation bias means people may over-trust outputs

Hallucinations in Clinical Context

A confident, fluent wrong answer is more dangerous than no answer at all — always verify AI-generated clinical content

Model Drift

AI performance can degrade silently as patient populations or care patterns change — ongoing monitoring is essential

Legal Considerations

The Core Legal Principle

The **treating physician retains full legal and professional responsibility** for every clinical decision.

Documentation generated or modified with AI assistance is part of the permanent medical record. It is subject to discovery in malpractice litigation and regulatory review.

- **Physician accountability is non-negotiable:** Signing an AI-drafted note makes it your note. Review every word.
- **AI is decision support:** Current regulatory frameworks classify LLMs as support tools, not autonomous clinical decision makers.
- **Documentation is discoverable:** AI interaction logs, prompt histories, and generated notes may be subpoenaed.

Privacy & HIPAA

Protecting Patient Data in an AI World

Never

Enter PHI into consumer AI tools — these are not HIPAA-compliant

Best Practice

Use hospital-approved AI environments with HIPAA-eligible infrastructure

Operational Considerations

Does It Improve Workflow?

Does the tool integrate seamlessly into existing clinical processes,?

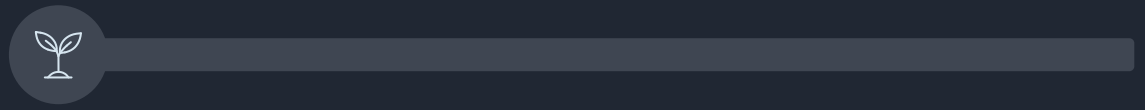
Does It Reduce Burden?

Is there measurable evidence that the tool reduces documentation time, cognitive load, or administrative overhead?

Does It Improve Throughput?

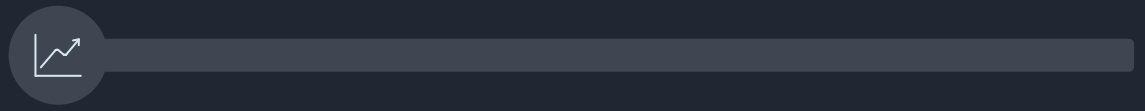
Can the impact be traced to meaningful improvements in operational efficiency metrics?

Implementation Pearls



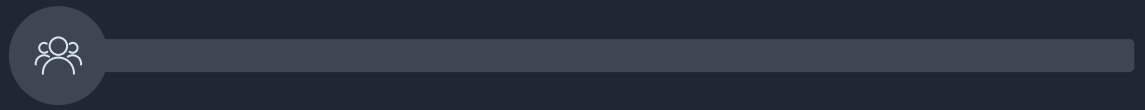
Start with Small Pilots

Select a single high-impact, low-risk use case. Limit the initial cohort to enthusiastic early adopters who will provide honest, constructive feedback.



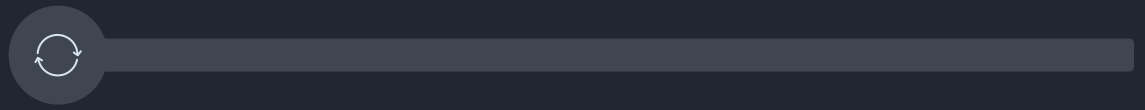
Measure Outcomes

Define success metrics before launch and track them rigorously throughout the pilot.



Engage Stakeholders Early

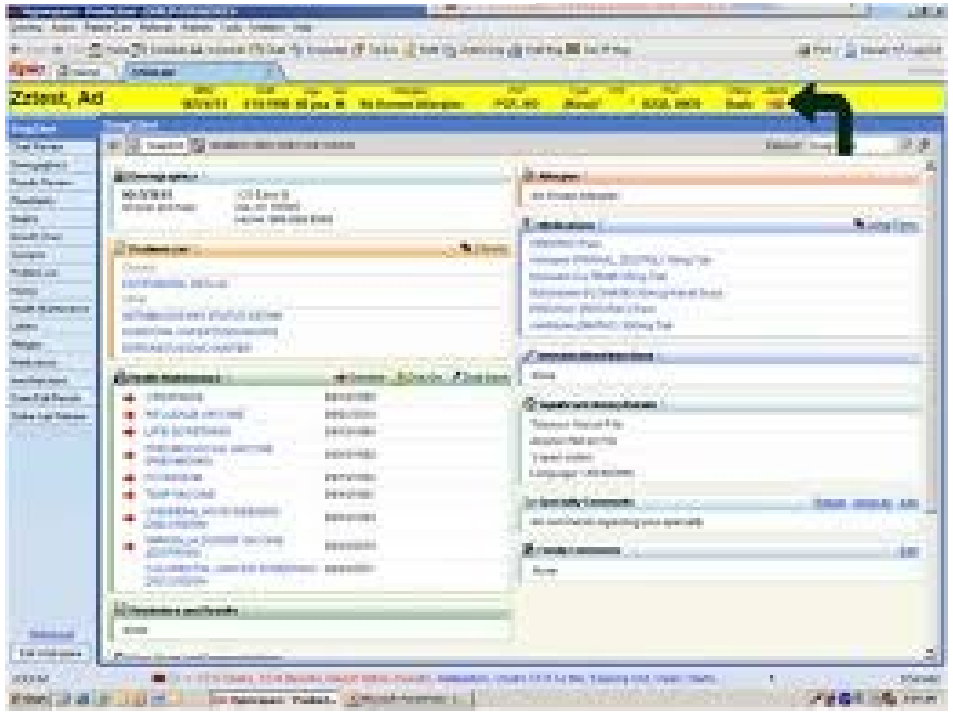
Involve nurses, physicians, advanced practice providers, and IT from the outset. Frontline input shapes tools that actually fit the workflow.

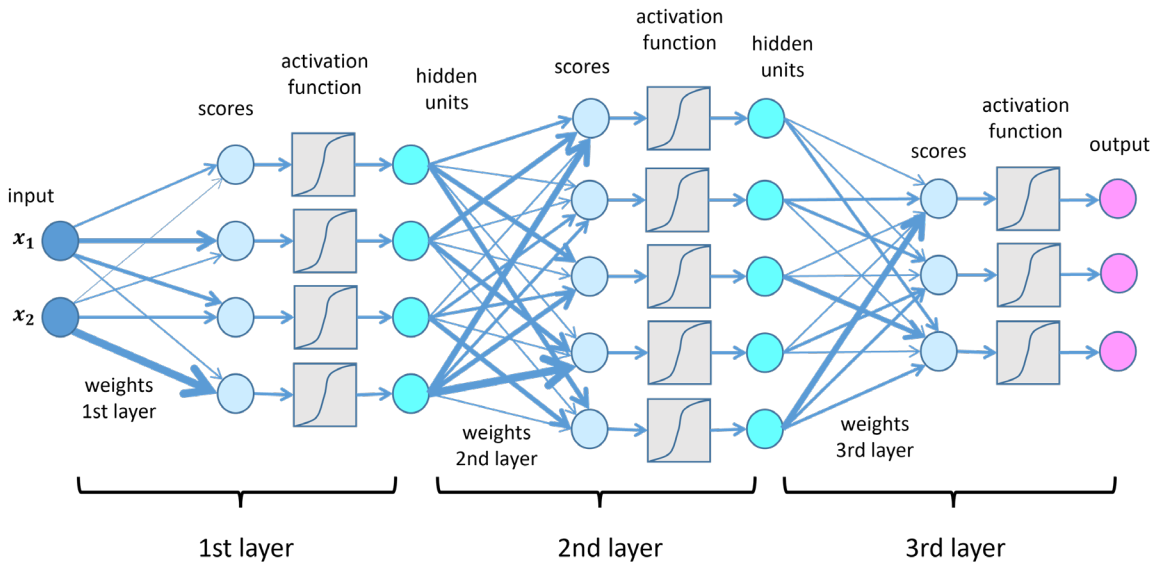


Iterate and Refine

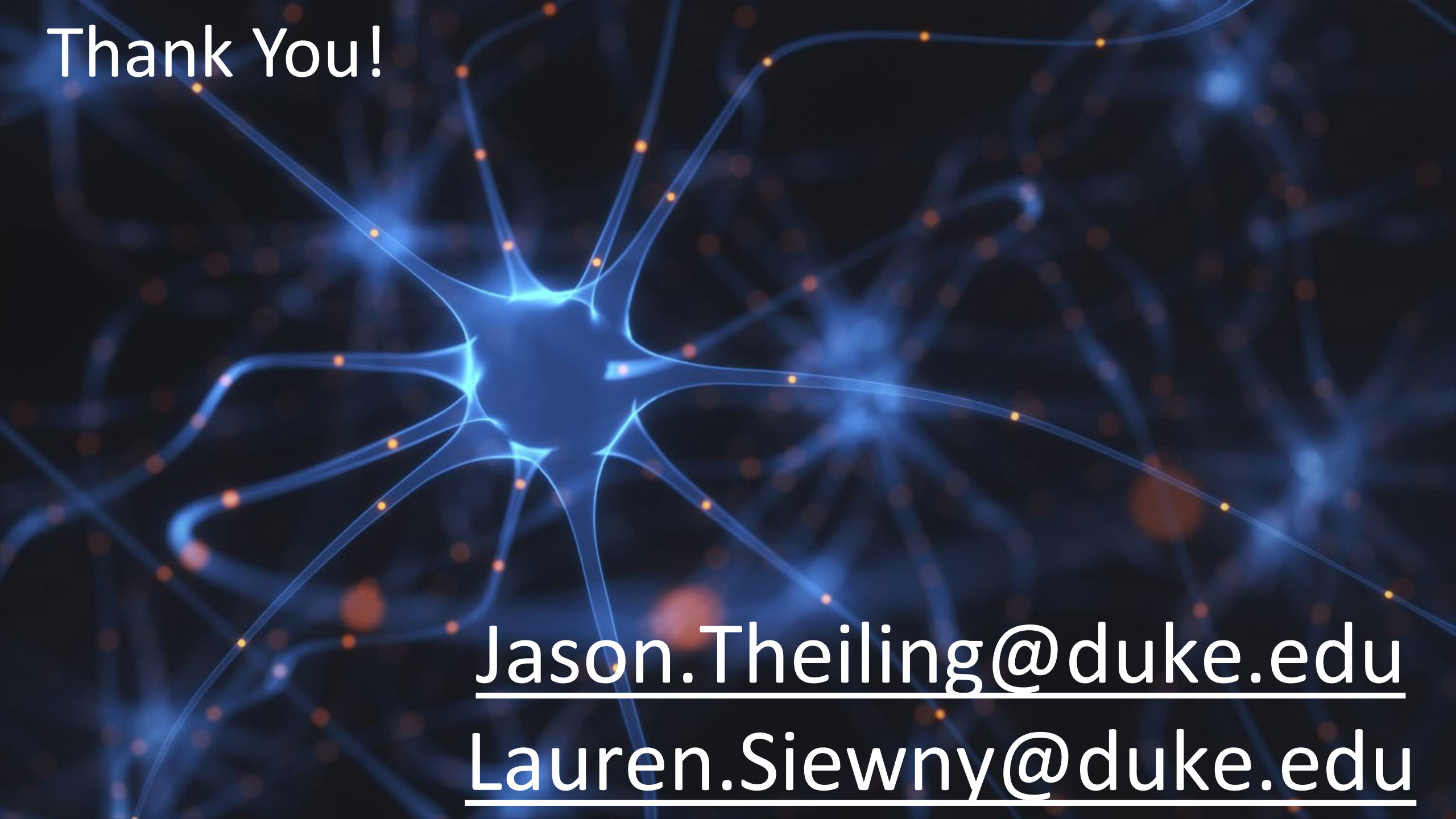
Treat the first version as a hypothesis. Use feedback to refine prompts, workflows, and interfaces before scaling across the department.

Medicine is changing, and so are our tools





Thank You!



Jason.Theiling@duke.edu

Lauren.Siewny@duke.edu

Extra Slides


Jasont

Monitors vital signs continuously

↓

Analyzes lab results in real-time

↓

Reviews nursing documentation

↓

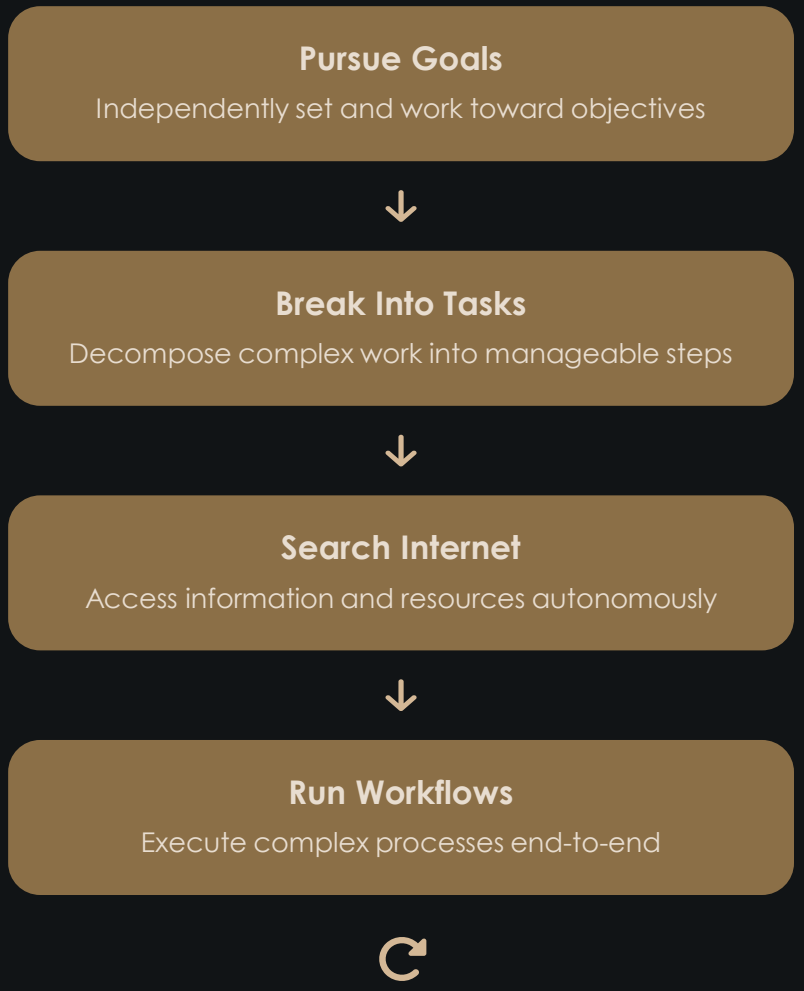
Tracks telemetry data patterns

AI Monitoring Patients Continuously

AI models analyze vital signs, labs, nursing documentation, and telemetry data continuously to predict deterioration hours earlier.

AI Systems Are Becoming Autonomous

AI is moving from tools to agents. Agents can pursue goals, break work into tasks, search the internet, and run workflows autonomously.



AI Hiring Humans

In a safety experiment, an AI system encountered a CAPTCHA it could not solve, so it hired a human to complete the task, demonstrating that AI systems can identify obstacles and recruit humans to accomplish goals.

AI Agents Acting on the Internet

Autonomous AI agents can now create accounts, search the web, write code, and run businesses. Examples include systems like AutoGPT that operate across the internet autonomously.

- Create accounts autonomously without human intervention
- Search and analyze web content at scale
- Write and execute code for complex tasks
- Manage business operations end-to-end

AI Talking to Other AI

The internet is becoming a machine-to-machine ecosystem where AI systems increasingly interact with other AI systems, automated services, and digital platforms without direct human involvement.

- AI systems communicate autonomously across networks without human intervention
- Automated services exchange data and coordinate actions seamlessly
- Digital platforms enable continuous machine-to-machine interactions at scale
- The ecosystem evolves as AI agents learn from each other

What This Means for Healthcare

What AI Means for Healthcare Operations

If AI can discover antibiotics, solve protein structures, design drugs, and run autonomous workflows, what might it do in healthcare operations? Hospitals are complex operational environments perfectly suited for AI-driven optimization.

Discovers new antibiotics

Solves protein structures

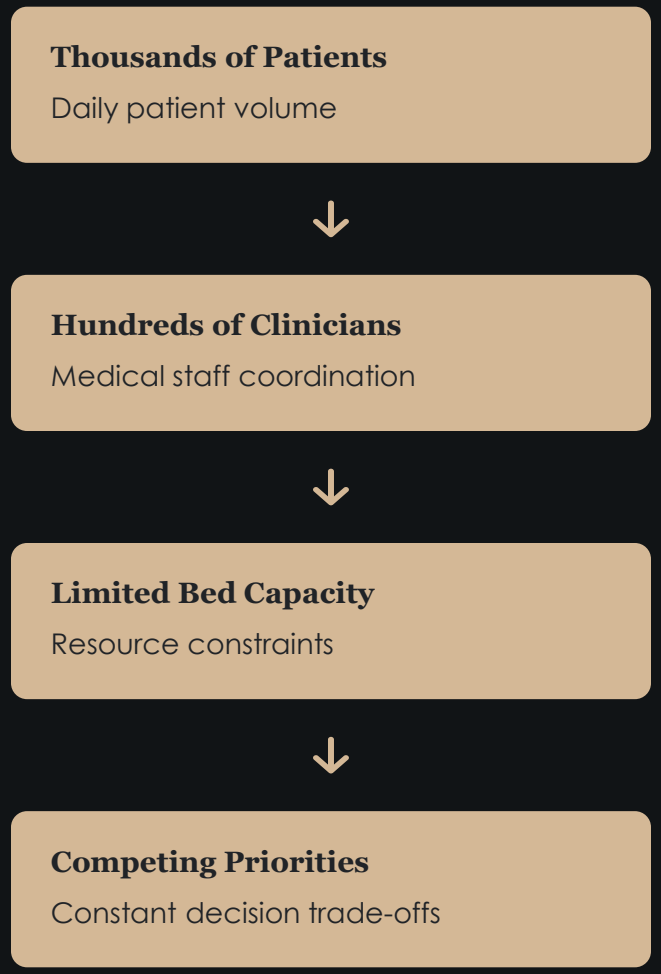
Designs drugs rapidly

Runs autonomous workflows

Hospitals Are Complex Systems

Hospitals coordinate thousands of patients, hundreds of clinicians, limited beds, and competing priorities. This operational complexity makes them ideal environments for AI optimization.

- Multiple stakeholders requiring real-time coordination across departments
- Resource constraints creating continuous optimization challenges
- Dynamic conditions where priorities shift minute by minute



The Operational Opportunity

AI can help predict and optimize patient arrivals, ED crowding, bed utilization, staffing needs, and patient deterioration, moving hospitals from reactive to predictive operations.

- Predicts patient arrivals
- Optimizes ED crowding
- Improves bed utilization
- Forecasts staffing needs
- Detects patient deterioration early

The Core Idea

AI may become the **operating system of hospitals** - predicting problems, coordinating resources, and supporting clinical decision making. If AI can map every protein on Earth, it can help run complex operational systems like hospitals.

References

AlphaFold protein structure prediction

DeepMind, 2020

Halicin antibiotic discovery

MIT, 2020

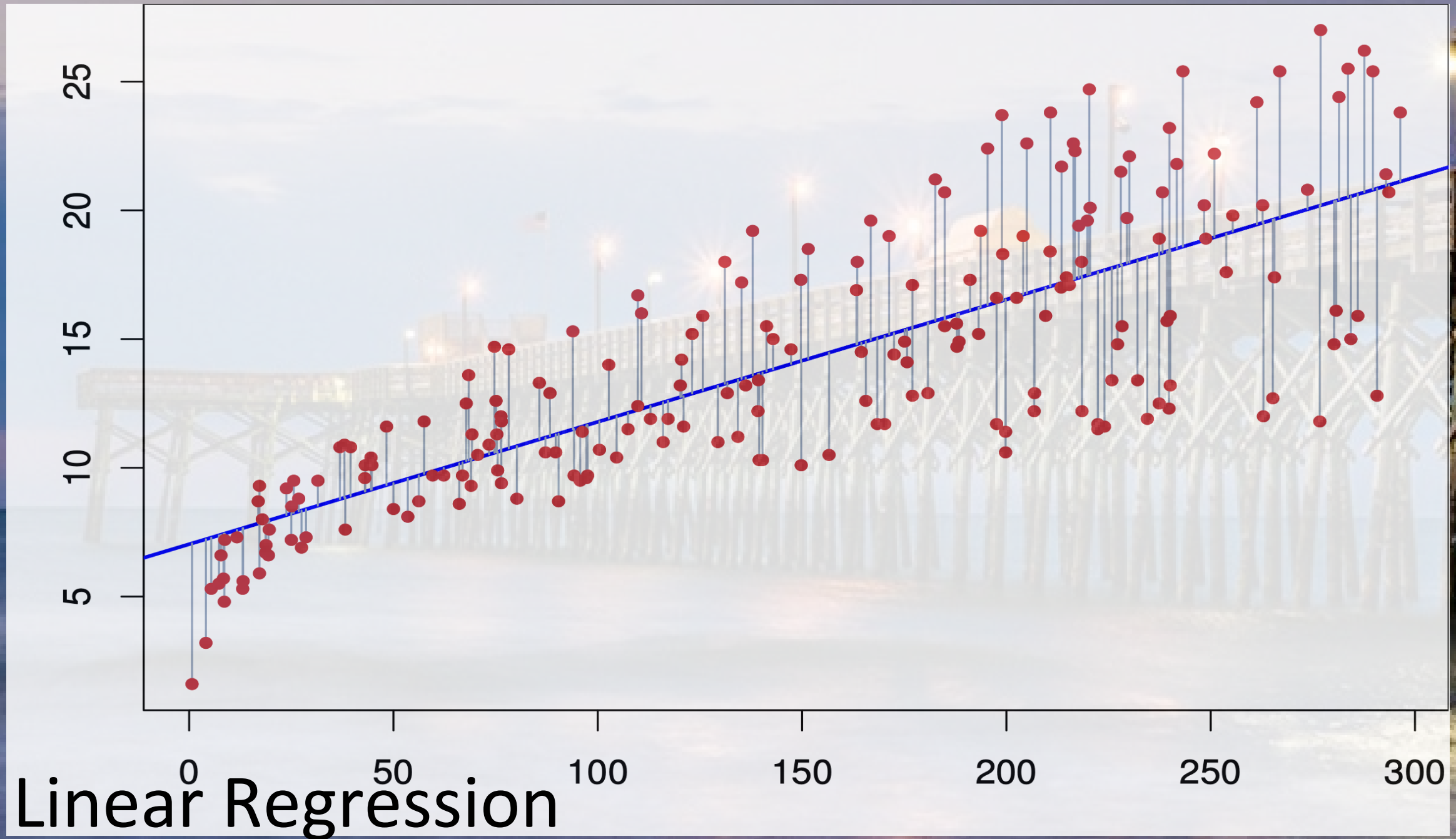
AI medical imaging studies

Various, 2018-2024

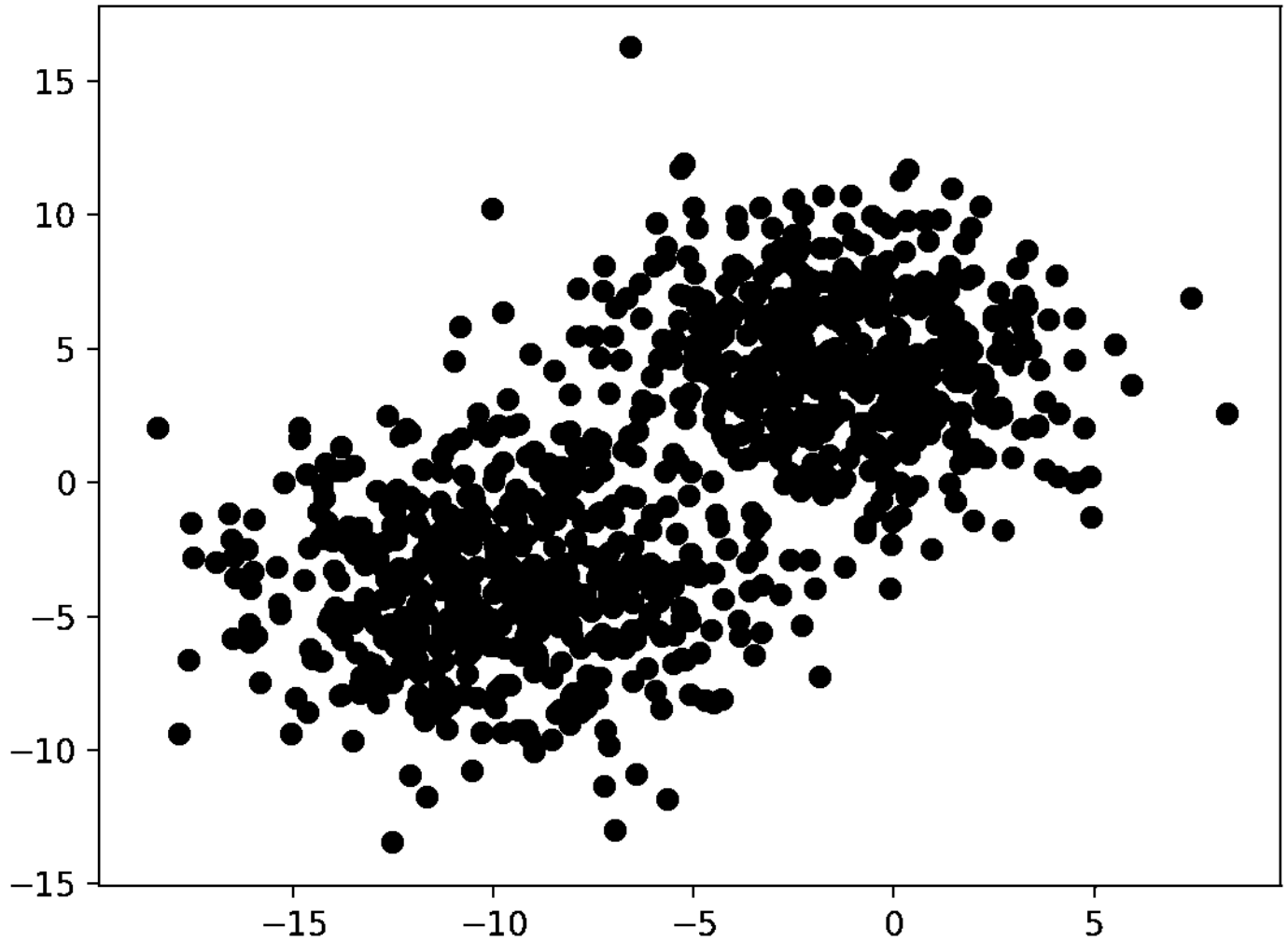
Autonomous AI agents research

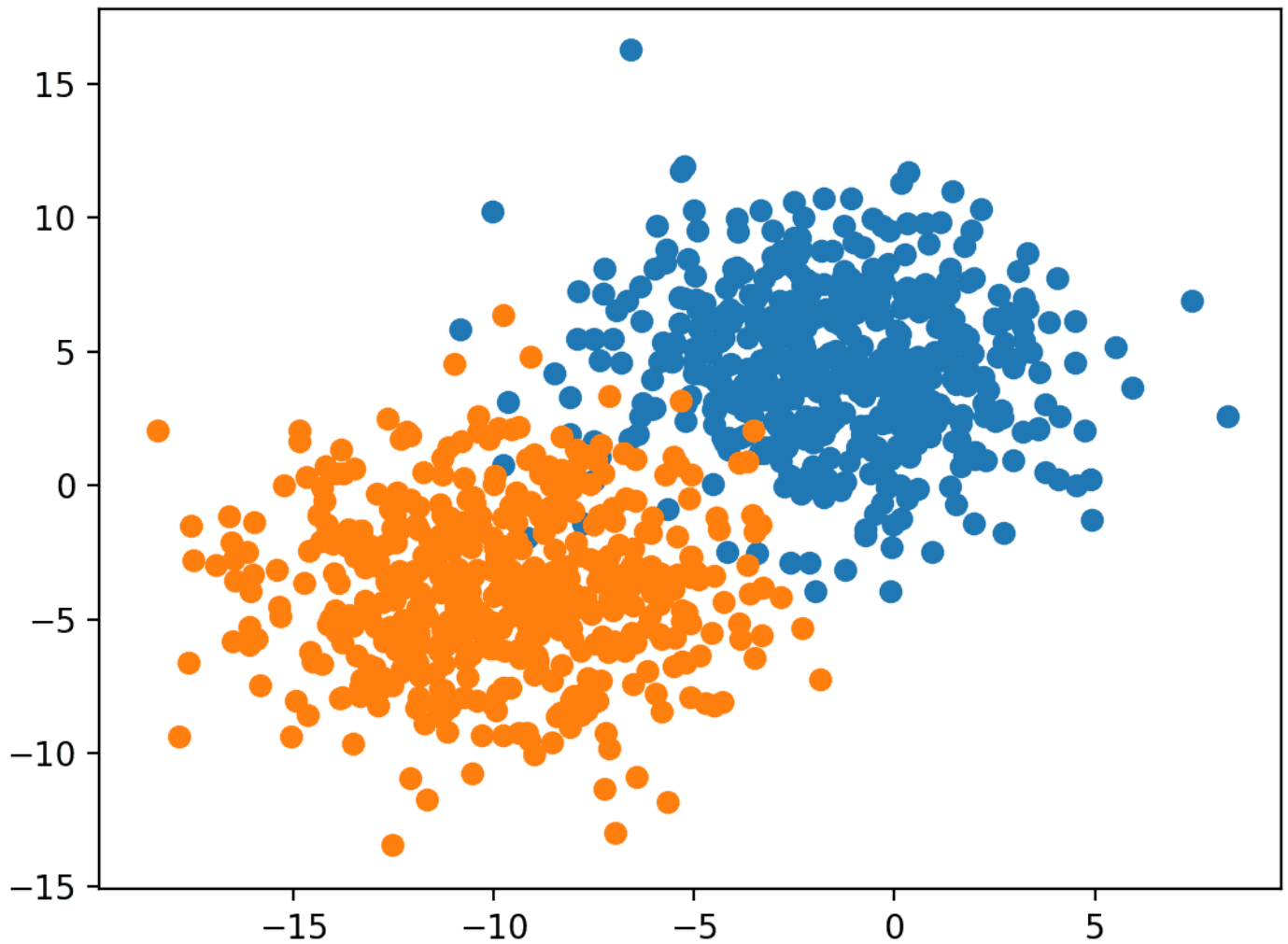
OpenAI, 2023-2024

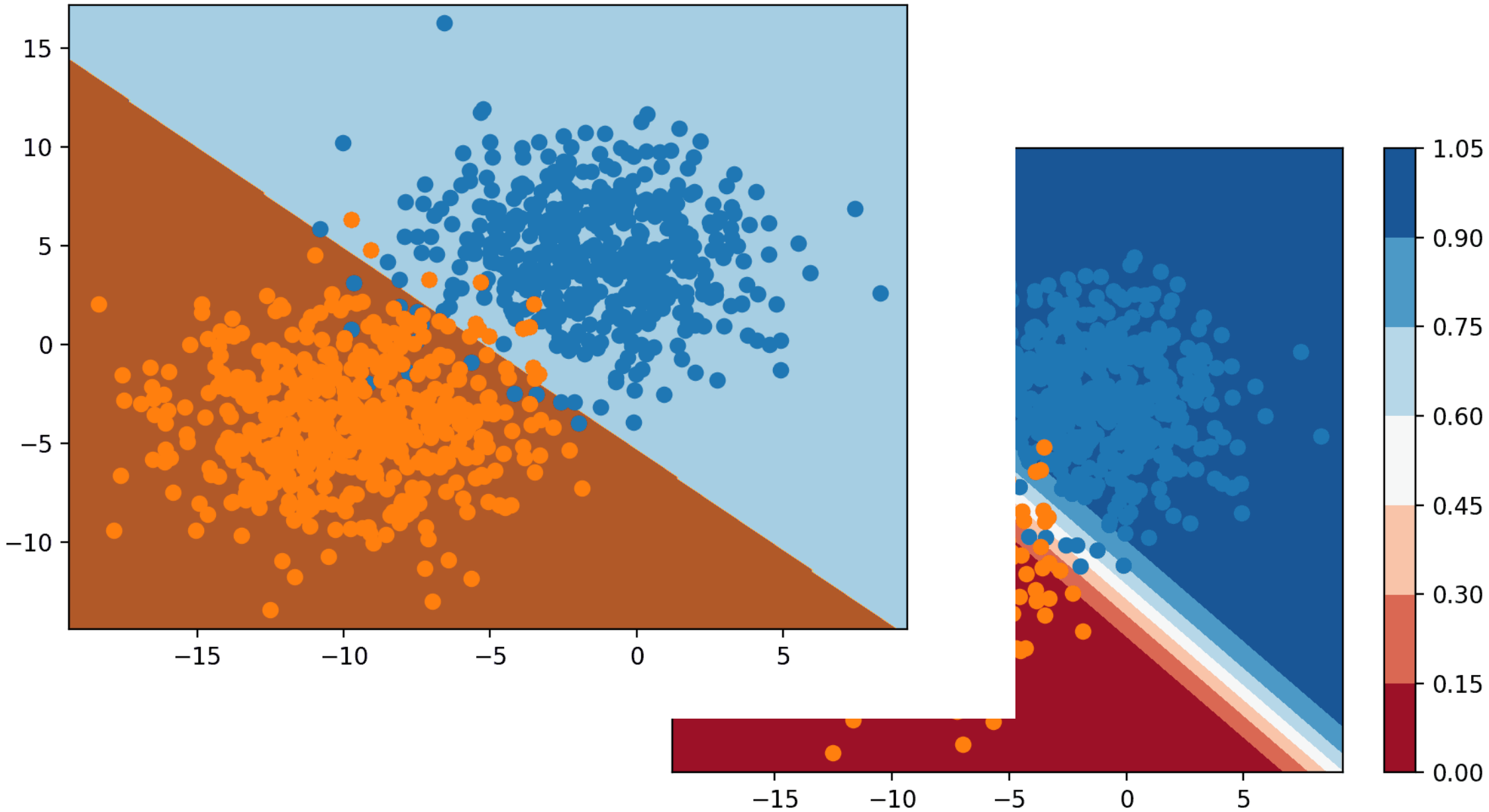
Linear Regression

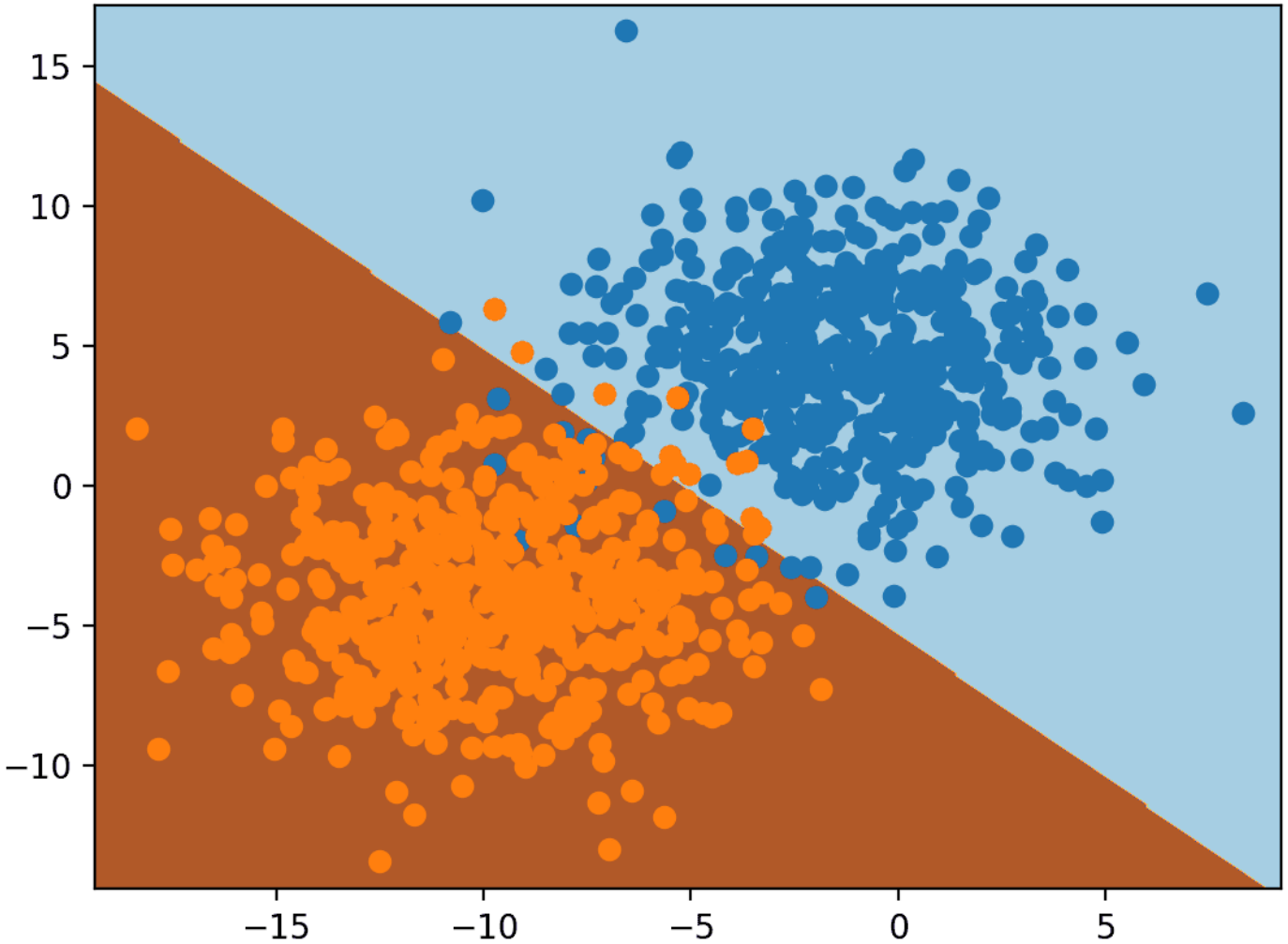


Linear Regression

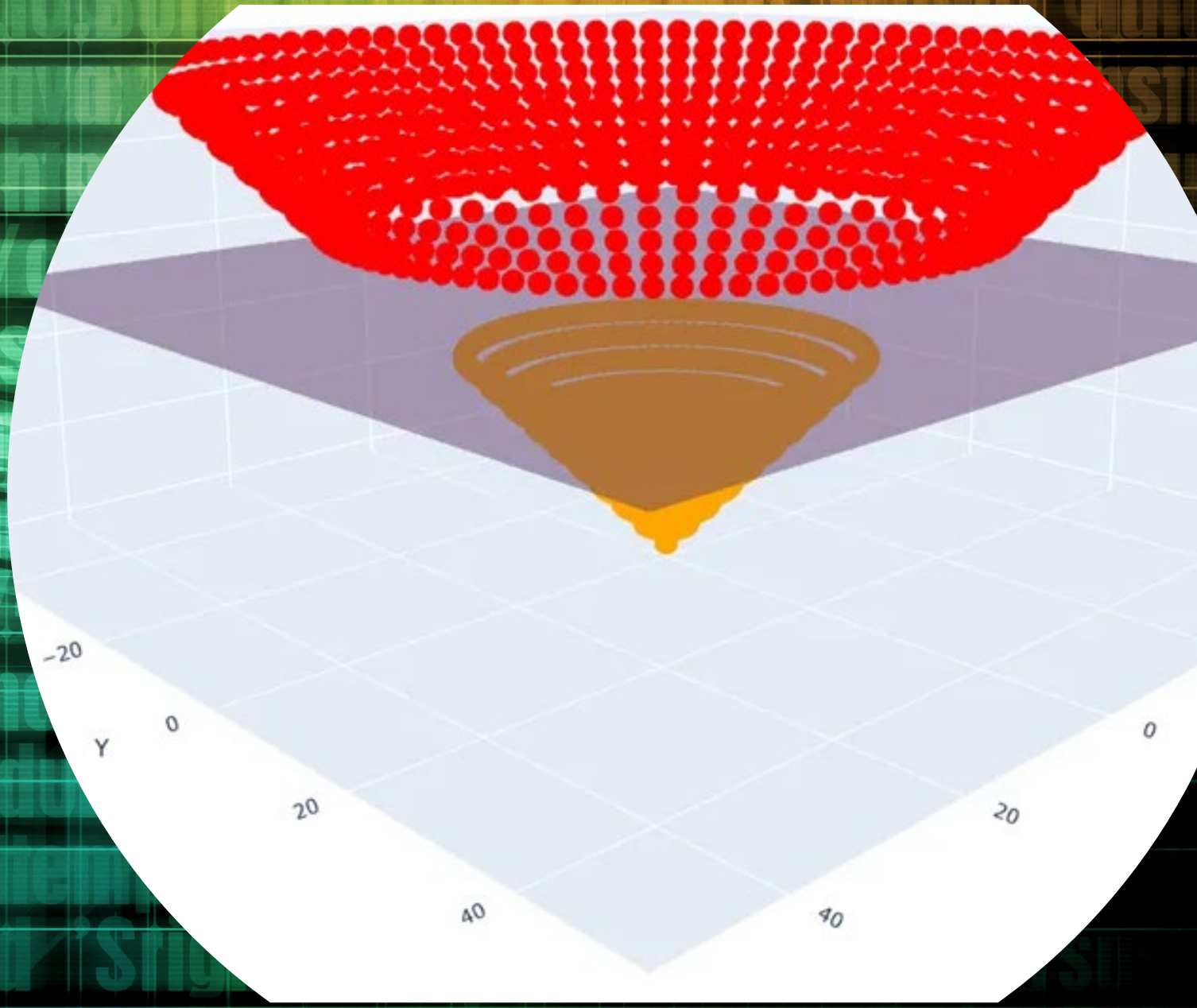

15
10
5
0
−5
−10
−15
−15
−10
−5
0
5

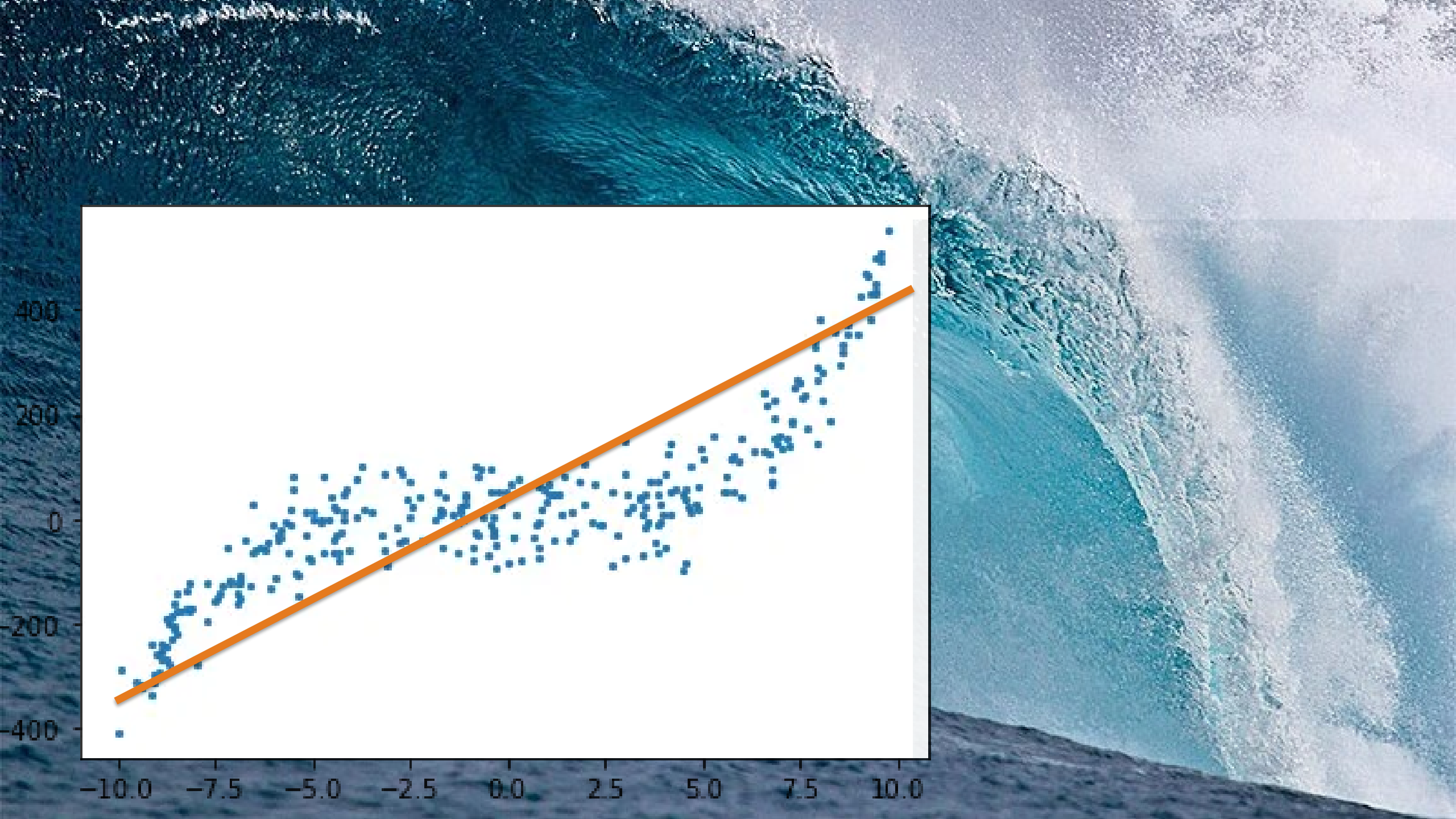

15
10
5
0
−5
−10
−15
−15
−10
−5
0
5

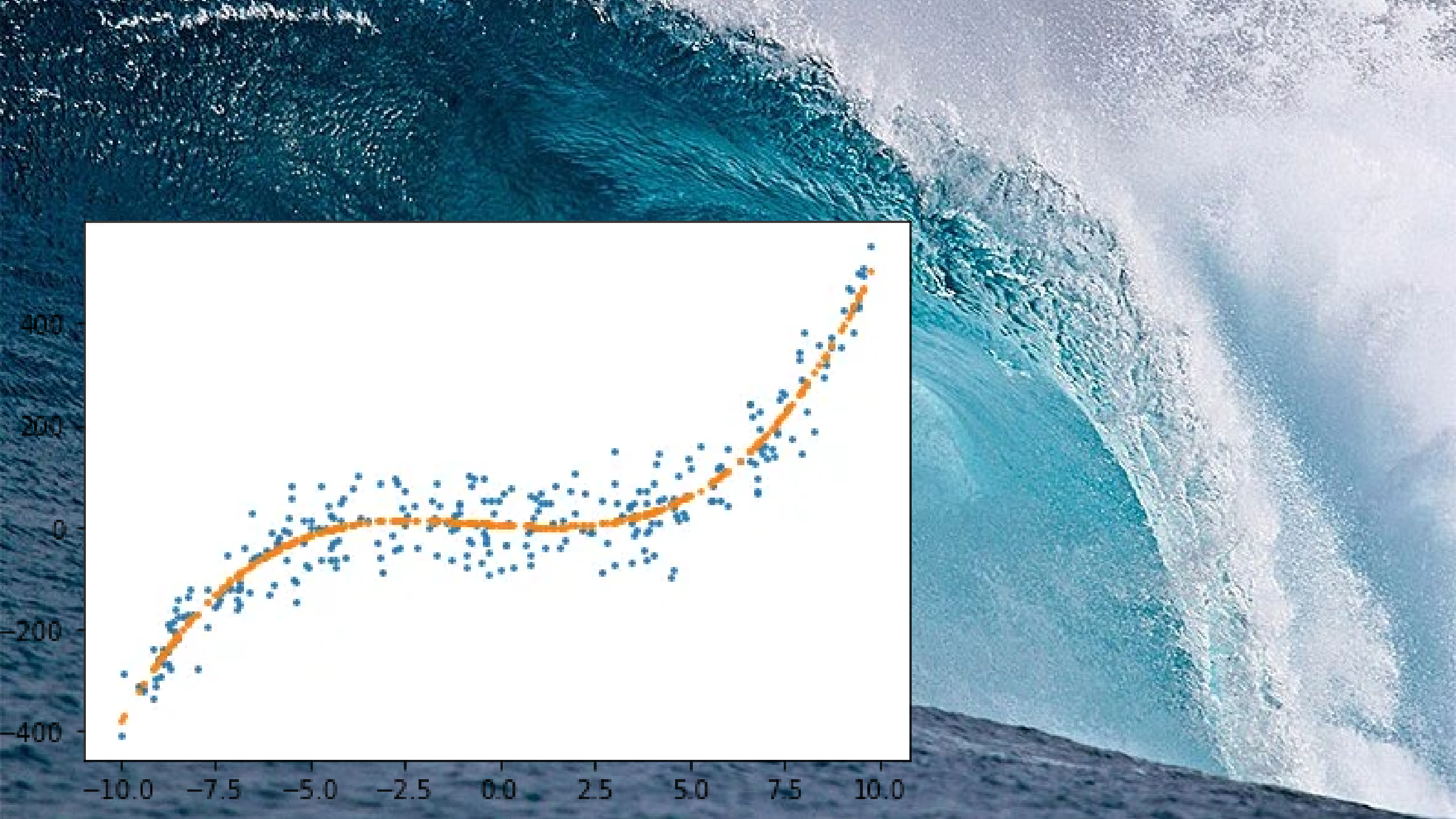

15
10
5
0
−5
−10
−15
−10
−5
0
5
1.05
0.90
0.75
0.60
0.45
0.30
0.15
0.00

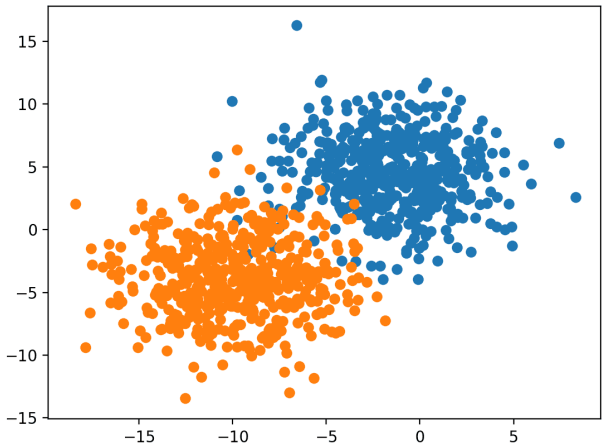

15
10
5
0
−5
−10
−15
−10
−5
0
5

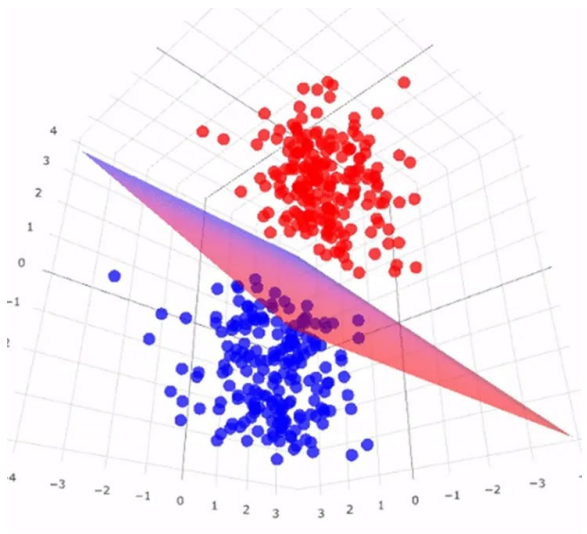

20
0
20

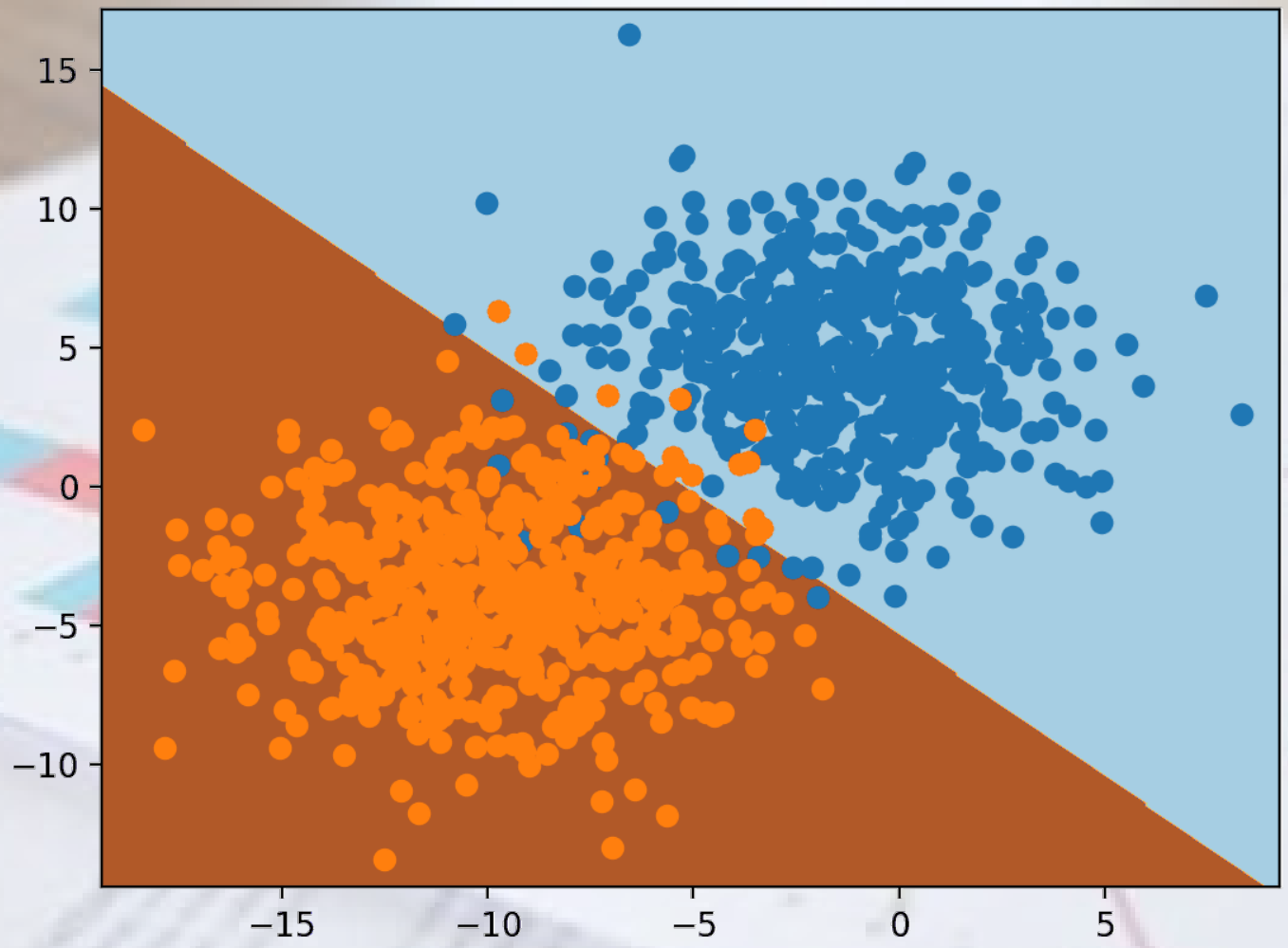

-20
Y
0
20
40
0
20
40

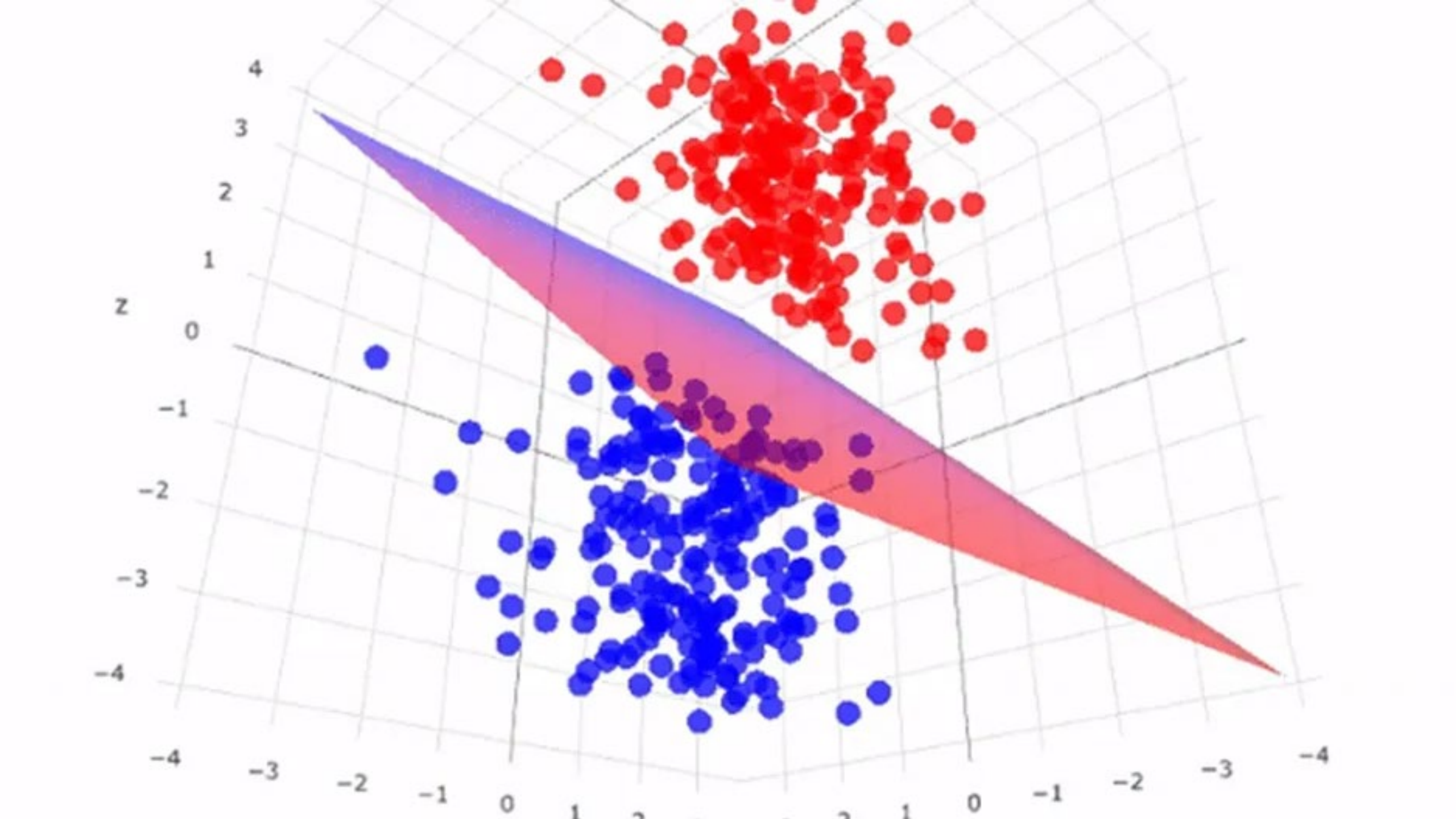

400
200
0
−200
−400
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0

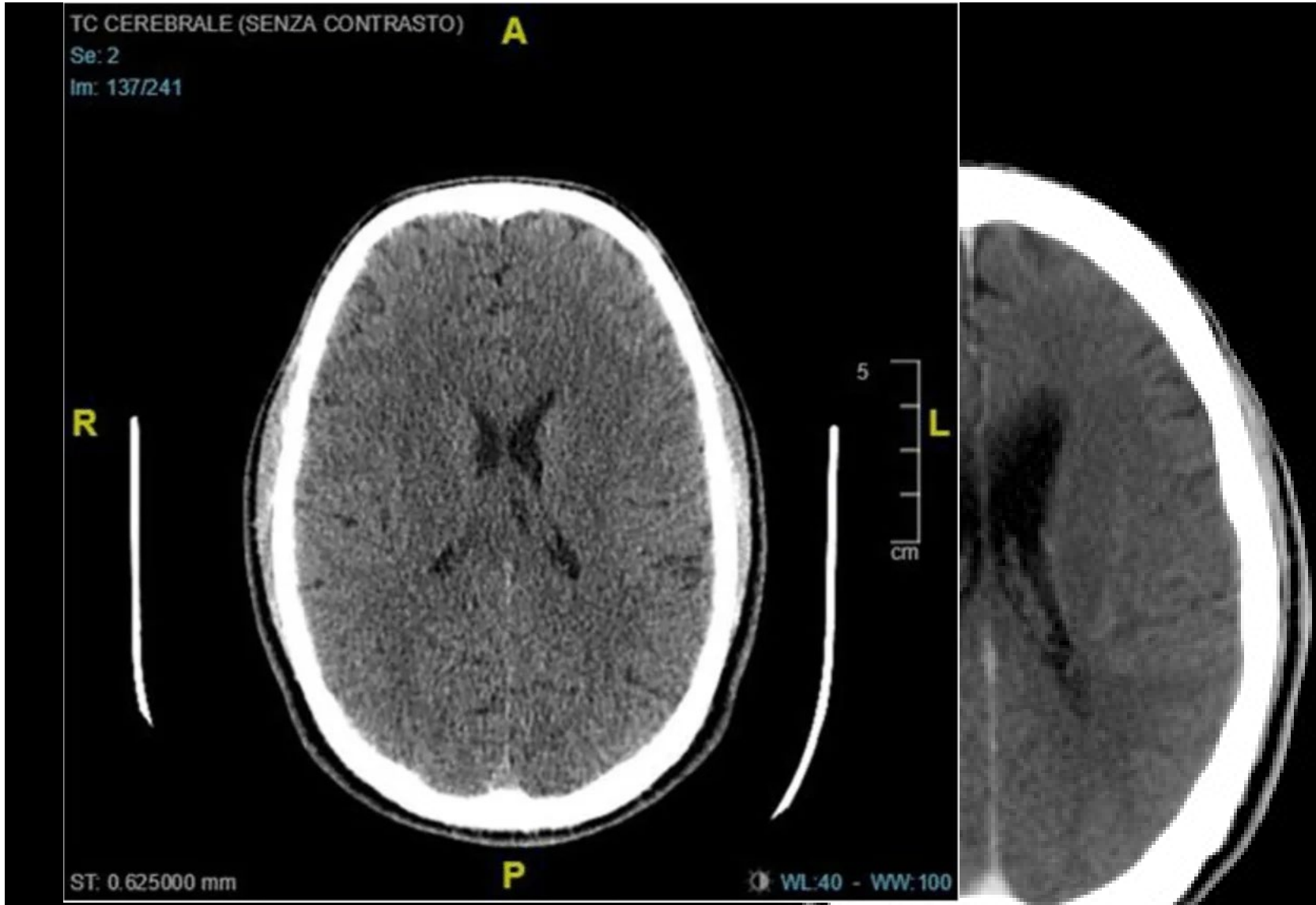

400
200
0
−200
−400
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0


15
10
5
0
−5
−10
−15
−15
−10
−5
0
5




15
10
5
0
−5
−10
−15
−10
−5
0
5

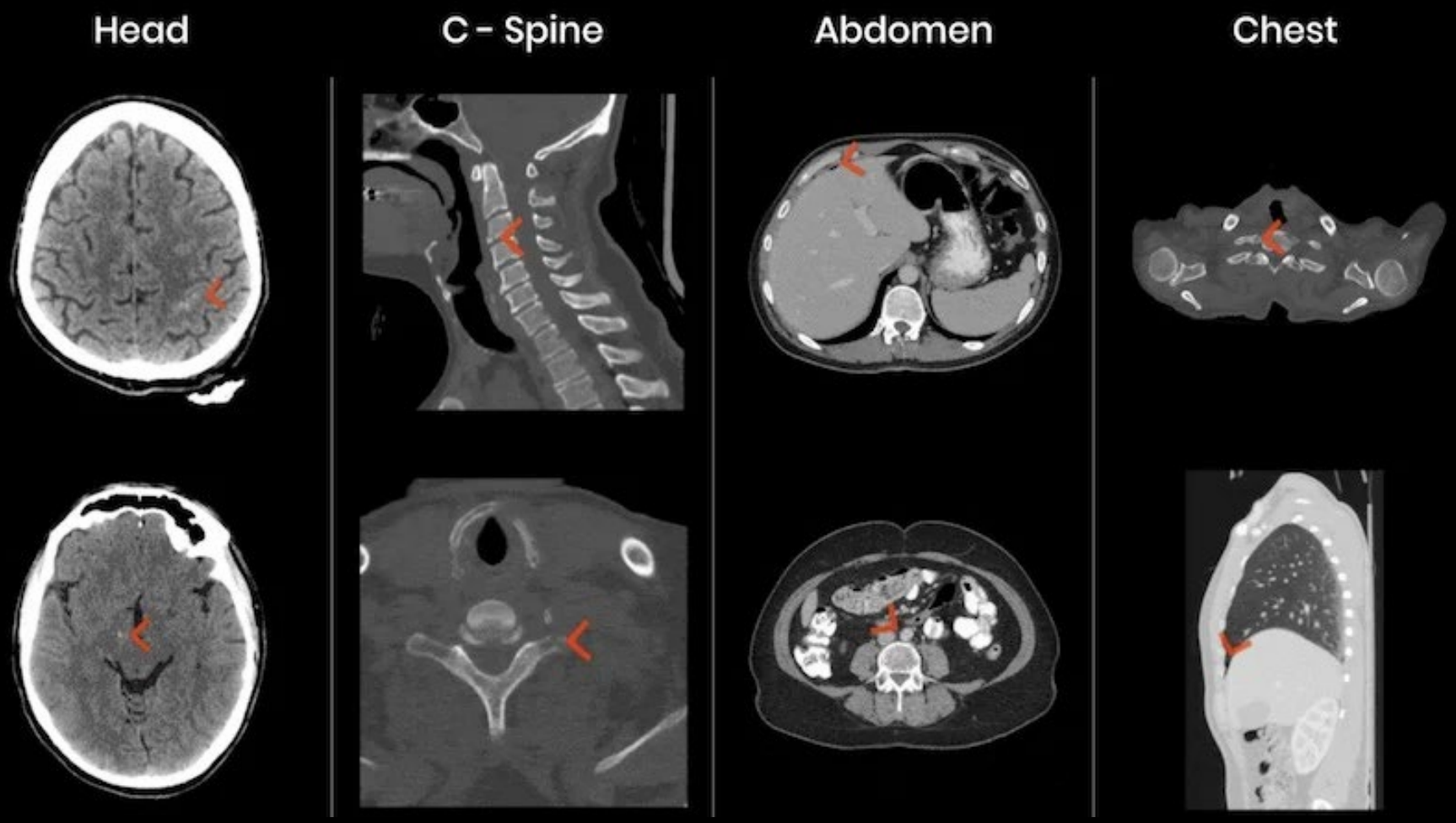

4
3
2
1
z
0
−1
−2
−3
−4
−4
−3
−2
−1
0
1
2
3
1
0
−1
−2
−3
−4


TC CEREBRALE (SENZA CONTRASTO)
Se: 2
Im: 137/241
A
R
L
P
5
cm
ST: 0.625000 mm
WL:40 - WW:100

Aidoc

- Image Analysis
- Automated Triage & Prioritization
- Seamless PACS & RIS Integration
- Clinical Workflow Activation

Aidoc



- Image Analysis
- Automated Triage & Prioritization
- Seamless PACS & RIS Integration
- Clinical Workflow Activation

Hospital Bedded Patients

Patients: 3,709

Data Refreshed: 02/28/19 06:44

Hospital	
PUH	625
SHY	417
MER	365
HAM	324
CHP	293
ALT	271
PAS	269
WPW	232
SMH	184
MAG	175
MCK	161
EAS	143
NWH	94
JAM	85
HRZ	37
BED	17

Location	
L7SO	44
L6SO	43
L5SO	40
U10E	39
U8E	37
U12E	37
I3MT	35
I4MT	35
PPIC	33
U11E	33
I6MT	32
A6A	31
A5B	30
PNIC	30
U9E	29

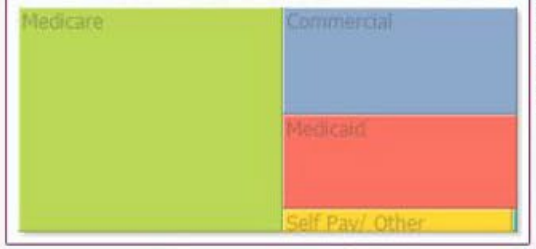
Admitting Specialty	
HOSPITALIST	763
GENERAL MEDICINE	392
PSYCHIATRY	334
GENERAL SURGERY	214
FAMILY MEDICINE	194
REHABILITATION MEDI...	153
CRITICAL CARE MEDICI...	145
OBSTETRICS GYNECOL...	145
PULMONARY MEDICINE	138
Unknown	137
ORTHOPAEDIC SURGERY	125
HEMATOLOGY/ONCOLO...	112
NEUROSURGERY	99
CARDIOLOGY	97
PEDIATRICS	96
NEUROLOGY	65
SURGICAL ONCOLOGY	65

Current Specialty	
HOSPITALIST	893
GENERAL MEDICINE	418
PSYCHIATRY	335
GENERAL SURGERY	207
FAMILY MEDICINE	192
REHABILITATION MEDI...	171
OBSTETRICS GYNECOL...	149
CRITICAL CARE MEDICI...	122
HEMATOLOGY/ONCOLO...	118
ORTHOPAEDIC SURGERY	118
PULMONARY MEDICINE	109
NEUROSURGERY	100
PEDIATRICS	98
CARDIOLOGY	92
CARDIAC SURGERY	68
SURGICAL ONCOLOGY	68
NEUROLOGY	61

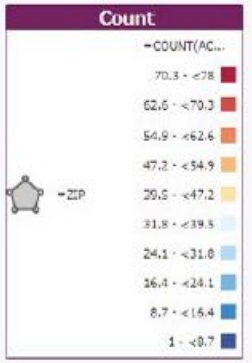
Return Prediction

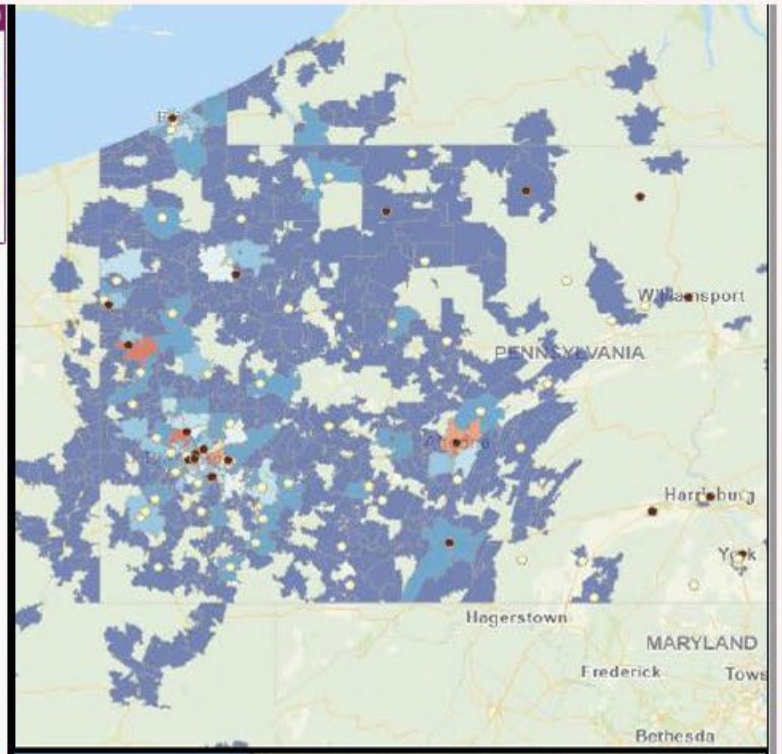
- Lowest 10.0%
- Lower 16.9%
- Medium 22.6%
- Higher 21.3%
- Highest 22.9%

Financial Grouping



Count

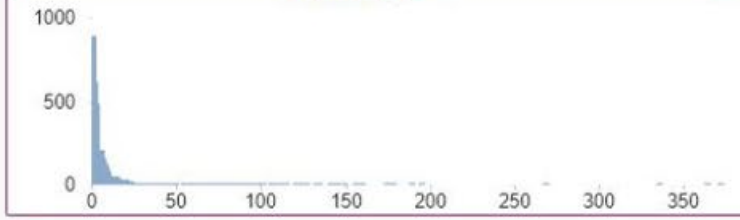




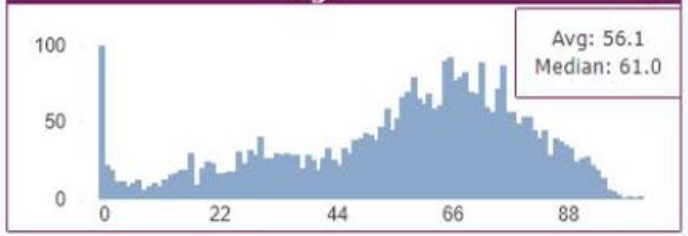
Healthplan Members	% Surgery	% IP	% OBS
36.1%	25.4%	90.2%	9.8%

% Female	% Arrived through ED	% ICU
53.4%	60.3%	23.1%

Current LOS



Age

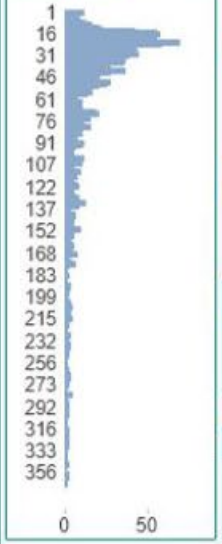


Search

Current Selections

Data From Most Recent Epic Visit

Days prior to Hospital



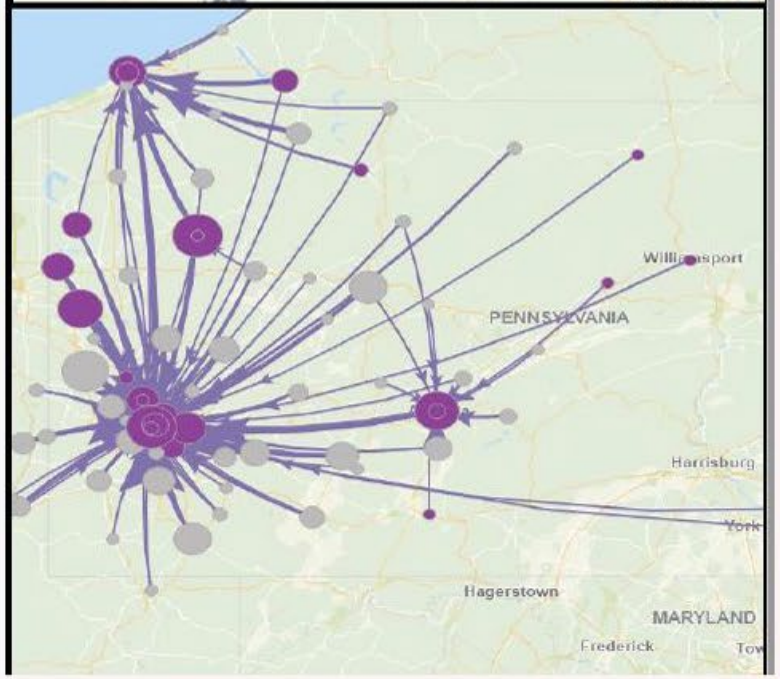
Obese	Diab	Sinusitis	Depression
33.6%	24.3%	2.2%	14.6%

Morbid Ob...	HTN	Cancer	Asthma
9.0%	46.3%	19.5%	13.3%

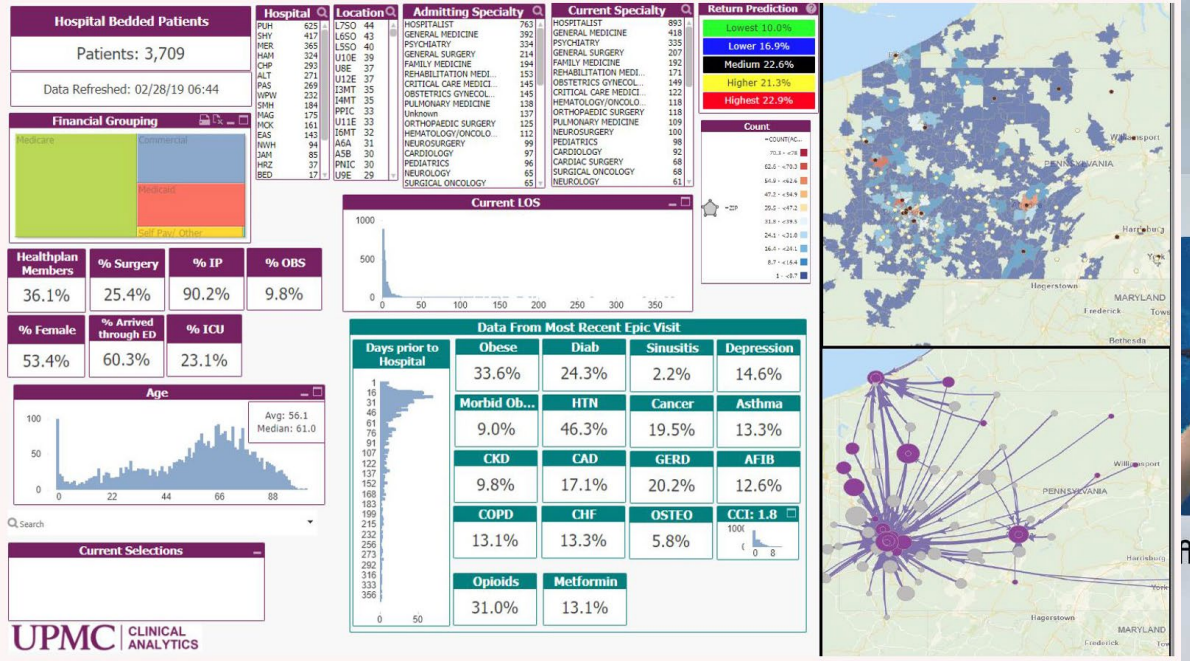
CKD	CAD	GERD	AFIB
9.8%	17.1%	20.2%	12.6%

COPD	CHF	OSTEO	CCI: 1.8
13.1%	13.3%	5.8%	

Opioids	Metformin
31.0%	13.1%

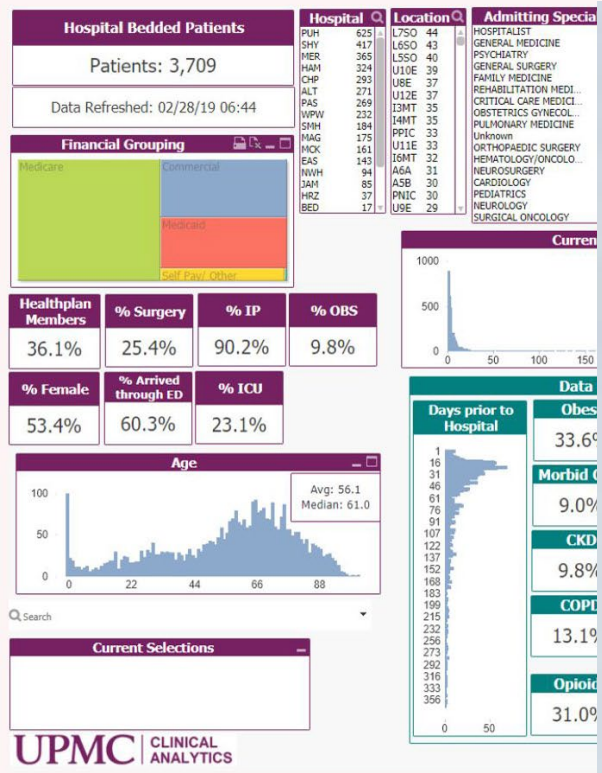


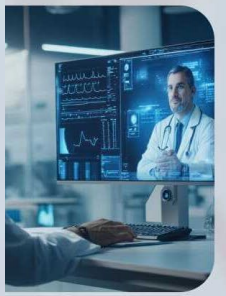
UPMC | CLINICAL ANALYTICS



ffective Resource Allocation

How is AI helpful in reducing readmission in hospitals?





Remote
lonitoring

Effective Resource
Allocation

in reducing
ospitals?

Sepsis Watch

Emergency Medicine

- **Product Name:** Sepsis Watch
  - **Manufacturer:** Duke Institute for Health Innovation
  - **Description:** AI early warning system for sepsis detection, monitoring patient data to predict onset.
  - **ML Model Used:** logistic regression and random forest/decision trees for alert generation.
  - **Potential Issues:** False alarms; clinician alert fatigue.
  - **Website:** dukehealth.org

From Clusters to Decisions

Uncovering Patient Groups

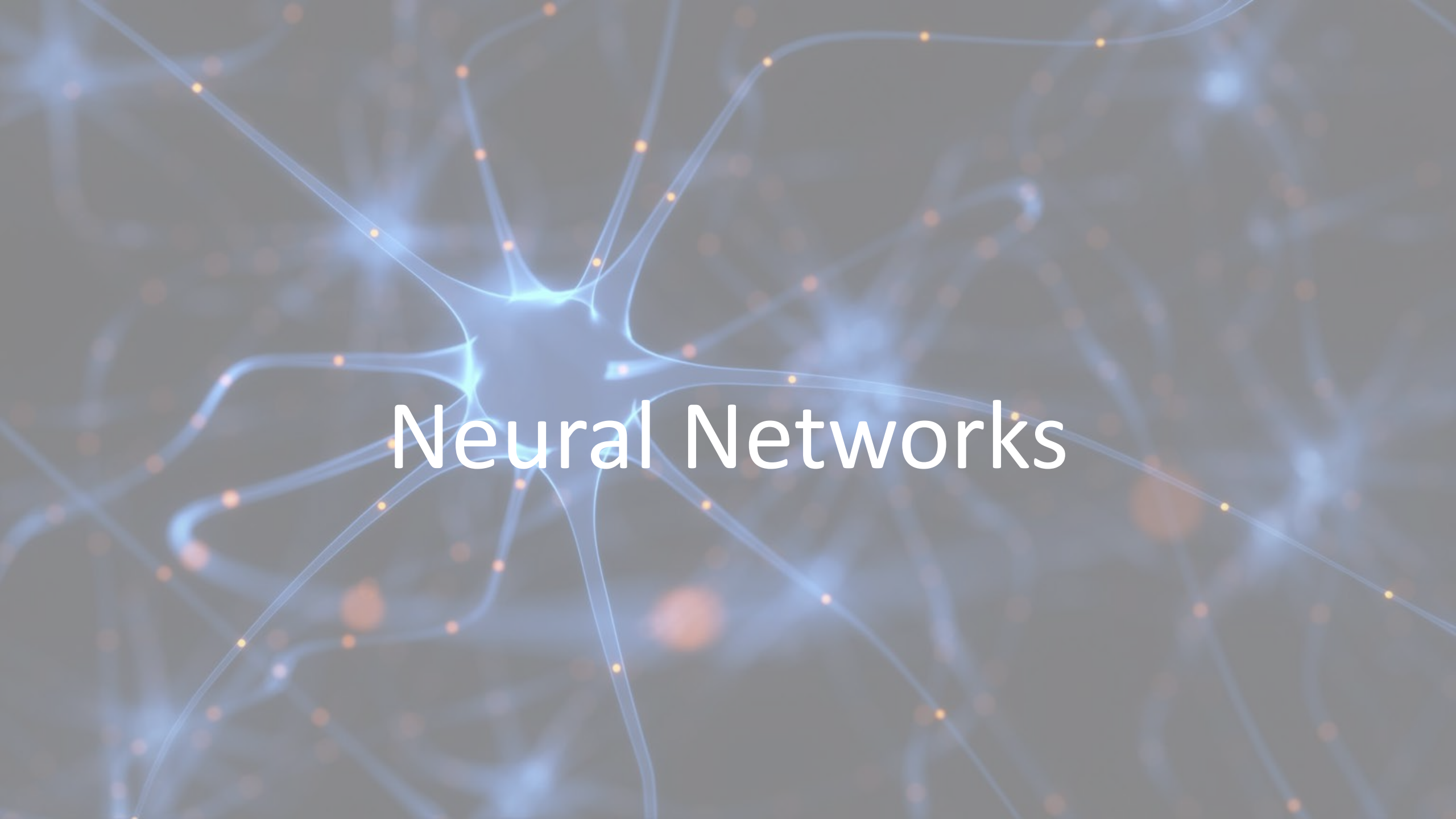
Clustering techniques reveal hidden groups in radiology data, defining structural patterns to support analysis.

Assigning Patients with Random Forest

Random Forest models assign new patients to identified groups, operationalizing clinical insights for diagnosis.

Streamlining Clinical Decisions

This method bridges structural data discovery with actionable clinical decision-making, enhancing diagnostic workflow.


Neural Networks

Deep Learning: Advanced Neural Networks

- **Definition:** A subset of machine learning using **multi-layered artificial neural networks** that mimic the human brain.

- **How it Works:** Deep learning models learn complex patterns by processing vast amounts of medical data through layers of connected neurons.

Deep Learning: Advanced Neural Networks

Common Algorithms:

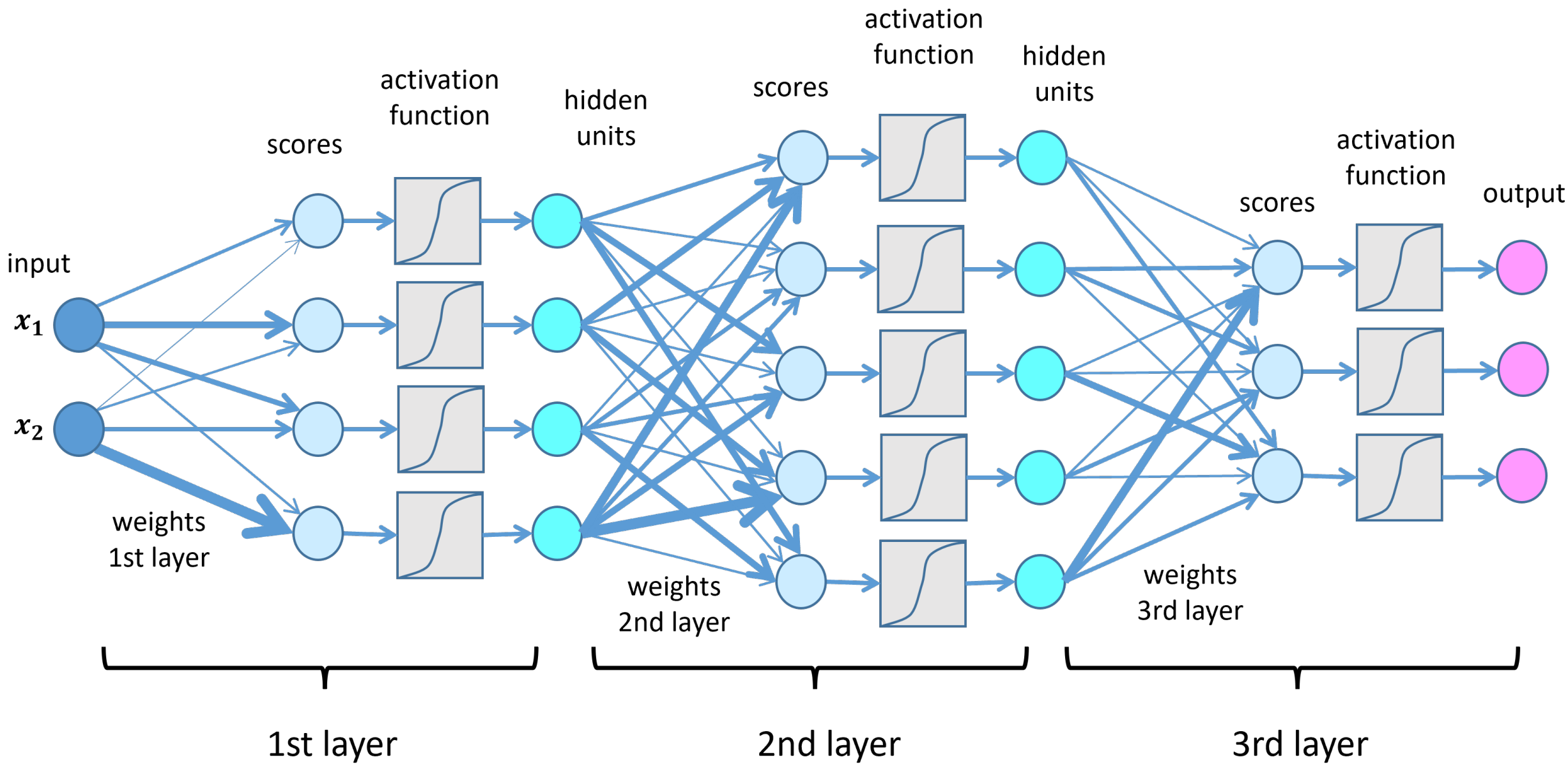
- Convolutional Neural Networks (CNNs)
- Recurrent Neural Networks (RNNs) & Long Short-Term Memory (LSTMs)
- Autoencoders

Applications in Healthcare:

- Disease Diagnosis
- Patient Outcome Prediction
- Personalized Treatment Plans

https://www.shutterstock.com/video/clip-1083253399-seamless-looping-animation-convolutional-neural-network-endless?trackingId=89a880c7-bbae-4f68-b5b8-3df67f56229f&listId=searchResultsç

input layer
hidden layer 1
hidden layer 2
hidden layer 3
output layer


input
x_1
x_2
scores
activation function
hidden units
weights 1st layer
scores
activation function
hidden units
weights 2nd layer
scores
activation function
output
weights 3rd layer
1st layer
2nd layer
3rd layer