

DataRobot



# Future directions of applied AI & implications for research

Ted Kwartler  
Chandler McCann

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**DataRobot**



# Ted Kwartler



Field, Chief Technology Officer



Shout out to Bob  
Baker circa 1997!



MBA



BB Gambling  
w/data



HARVARD  
Faculty of Arts and Sciences

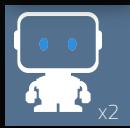
Adjunct, Data Mining for Business



Ops Mgr



x2  
AVP, ML Research



x2  
Miscellaneous

# Chandler McCann



Field, Chief Technology Officer





# Agenda

- 1. The hype cycle of AI!**
- 2. What about genAI (chatGPT)?**
- 3. AI in Research**
  - a. Emerging genAI tools
  - b. Clinical Recommendations for Spinal Cord Injury Surgery (PLOS One)
  - c. Informing Government decision making for improving access to drinking water
  - d. Common challenges with AI in research

# AI is often an interdisciplinary project requiring communication, qualitative, specific subject & technical expertise.



Planning & Strategy



Data Fluency



Build & Validate a Model



Deploy the Technology



Continuous Monitoring



Project Mgrs



Business Operations



Business Analysts



Data Engineers



Data Scientists



Software Developers



Dev Ops



IT



Business Users



Stakeholders



Risk and Compliance

## AI INNOVATORS

Liberal arts, business, communication/English & specialty knowledge i.e. healthcare

## AI CREATORS

Analytics, math

## AI OPERATORS

Computer science

## AI CONSUMERS

Ethics/Governance, English/Communication

# AI has extensive applicability



## AI in Finance:

Algorithmic Trading:  
Predictive Trading Strategies  
Fraud Detection:  
Identifying Suspicious Financial Activities  
Credit Scoring & Assessing Creditworthiness

## AI in Marketing:

Customer Segmentation:  
Targeted Marketing  
Recommendation Systems:  
Personalized Product Recommendations  
Predictive Analytics:  
Forecasting Market Trends

## AI in Education:

Adaptive Learning Systems  
Personalized Learning Paths  
Automated Grading:  
Grading Assignments and Exams

## Fairness in AI:

Addressing Bias in Algorithms  
Explainability  
Interpretable Machine Learning Models

## Human-AI Collaboration:

Augmented Intelligence  
Decision AI

## Enhancing Human Abilities with AI:

Exoskeletons and Wearable AI/Augmented Reality  
Assisting Human Physical Capabilities

## Expert Systems and Knowledge Representation:

Rule-Based Systems  
Inference Engines  
Knowledge Graphs Representing and Querying Knowledge

## AI in Healthcare:

Medical Imaging Analysis:  
Diagnosing Diseases from X-rays, CT Scans, etc.  
Drug Discovery  
Predicting Drug Candidates  
Healthcare Predictive Analytics:  
Patient Outcome Prediction  
Disease Progression Modeling

## Cybersecurity:

Identifying Suspicious Behavior  
Intrusion Detection Systems:  
Detecting Unauthorized Access  
Malware Analysis  
Identifying and Analyzing Malicious Software

## Natural Language Processing (NLP):

Named Entity Recognition (NER)  
Sentiment Analysis  
Machine Translation  
Text Summarization  
Part-of-Speech Tagging

## Image Recognition:

Object Detection  
Facial Recognition  
Threat detection

## Video Analysis:

Action Recognition  
Video Summarization  
3D Vision:  
Depth Sensing  
Structure from Motion

## Robotics and Automation:

Robotic Process Automation (RPA):  
Automating Repetitive Tasks  
Industrial Robots  
Self-Driving Cars  
Drones

AI is really a collection of technologies all requiring historical data to observe patterns\*.

*\*AI can even be used to create "synthetic data" mimicking the real world for use in other AI!*



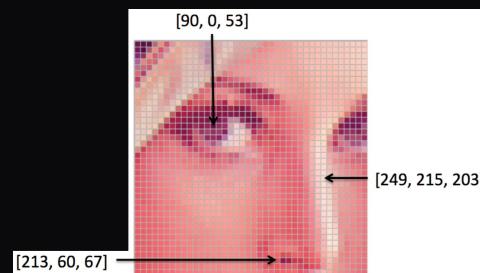
# AI is just pattern recognition, just like us!

## Vision

You aren't looking at the person. You look at groups of pixels & see recognizable patterns.



Every pixel have a RGB pixel value & groups of them are examined by the algorithm.



Multiple patterns can be identified simultaneously.

Minimum confidence: 80 % Maximum objects: 20

Blazer • Confidence: 100 %

Clothing • Confidence: 100 %

Coat • Confidence: 100 %

Jacket • Confidence: 100 %

Adult<sup>1</sup> • Confidence: 99 %

Male<sup>2</sup> • Confidence: 99 %

Click to enlarge

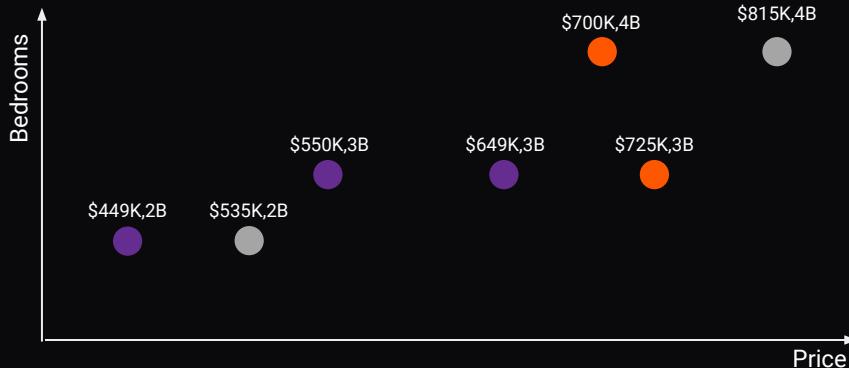
This is an algorithm called convolutional neural networks.



# AI is just pattern recognition, just like us!

## Real Estate Comps

- Condo
- House
- Unknown



This is an algorithm called K-Nearest Neighbor. Computers can look at thousands of factors simultaneously.



# AI Doomerism is a distraction

Data centers account for 2.5% to 3.7% of global GHG emissions

## OYAK Cement Boosts Alternative Fuel Usage from 4% to 30% — for Savings of Around \$39M



When a leading Turkish cement maker turned to AI for process optimization, the company identified and rolled out improvements that reduced cost, and most importantly, brought down CO<sub>2</sub> emissions nearly 200,000 tons per year.

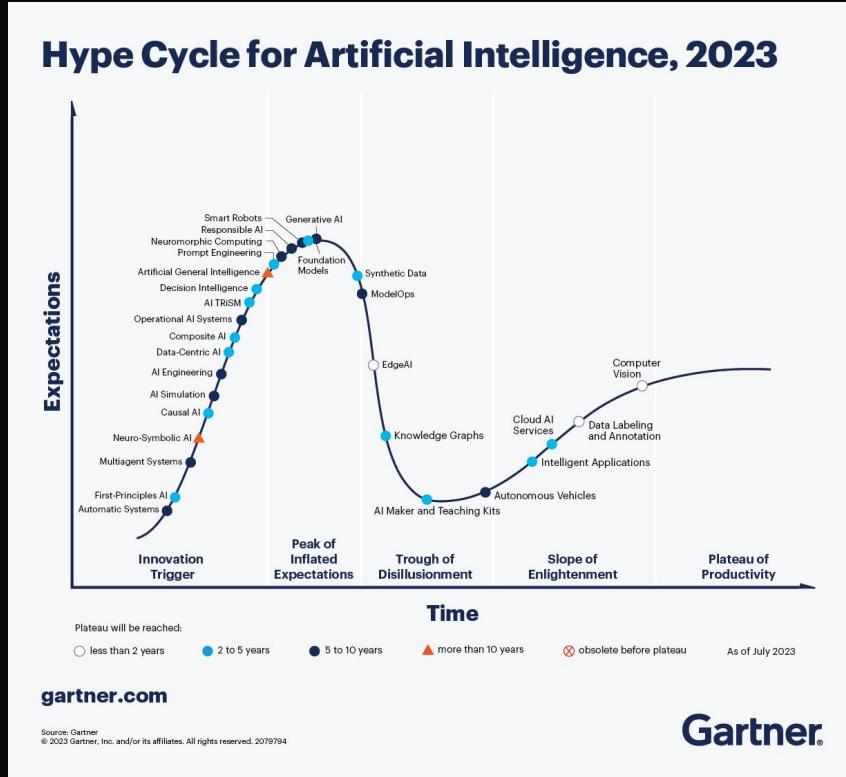
AI Research Survey:  
The median respondent believes the probability that the long-run effect of advanced AI on humanity will be "extremely bad (e.g., human extinction)" is 5%



How AI can save our humanity  
5,220,069 views | Kai-Fu Lee | TED2018 • April 2018

It can be blamed for everything & can also solve everything?! Other issues are more immediate than an imagined future of AGI singularity. Today AI is always single task focused.

# Isn't chatGPT/LLMs/genAI different & actually intelligent?



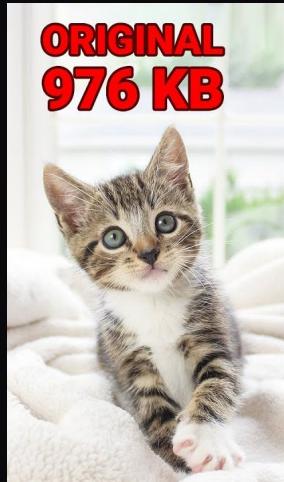
For the masses, we are at peak AI.

# GenAI Basics

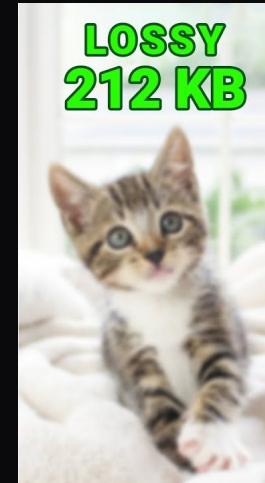
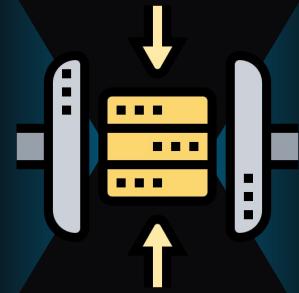
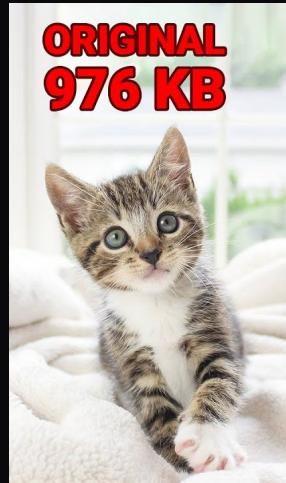


Who has used chatGPT personally, professionally? Stable Diffusion/Midjourney?

# Lossless Compression

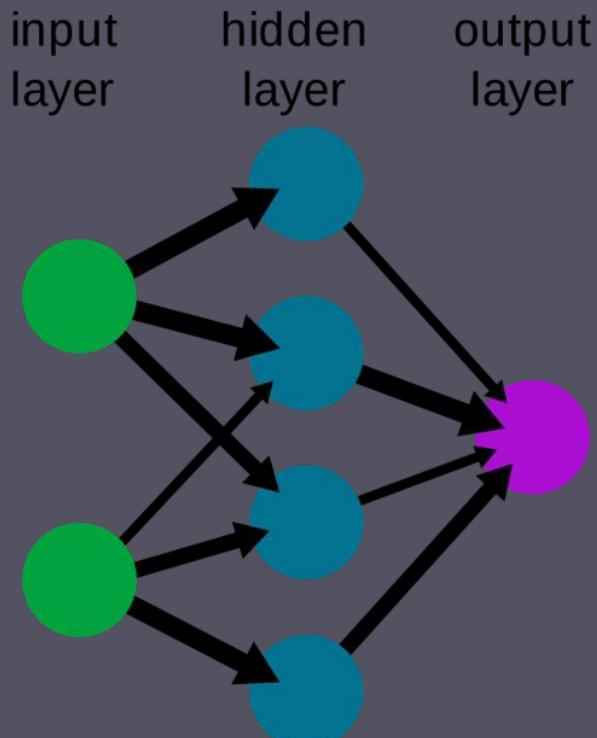


# Lossy Compression



An algorithm scans files & reduces their size by discarding irrelevant information.

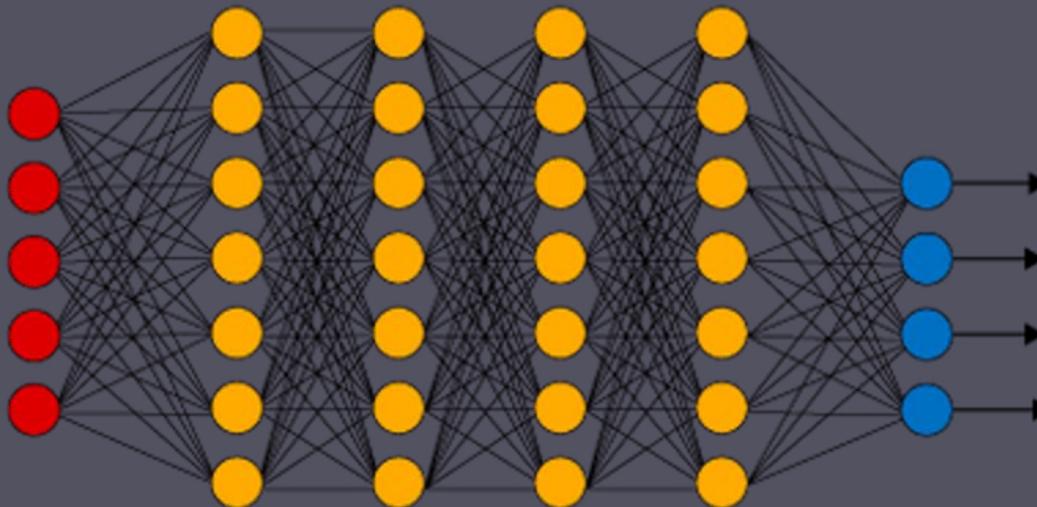
LLMs are built with Neural Networks to compress information.



# Neural Networks can have billions of connections.



## Deep Learning Neural Network



Each perceptron has an activation function within it learned from patterns found in the data.



input1 = .2

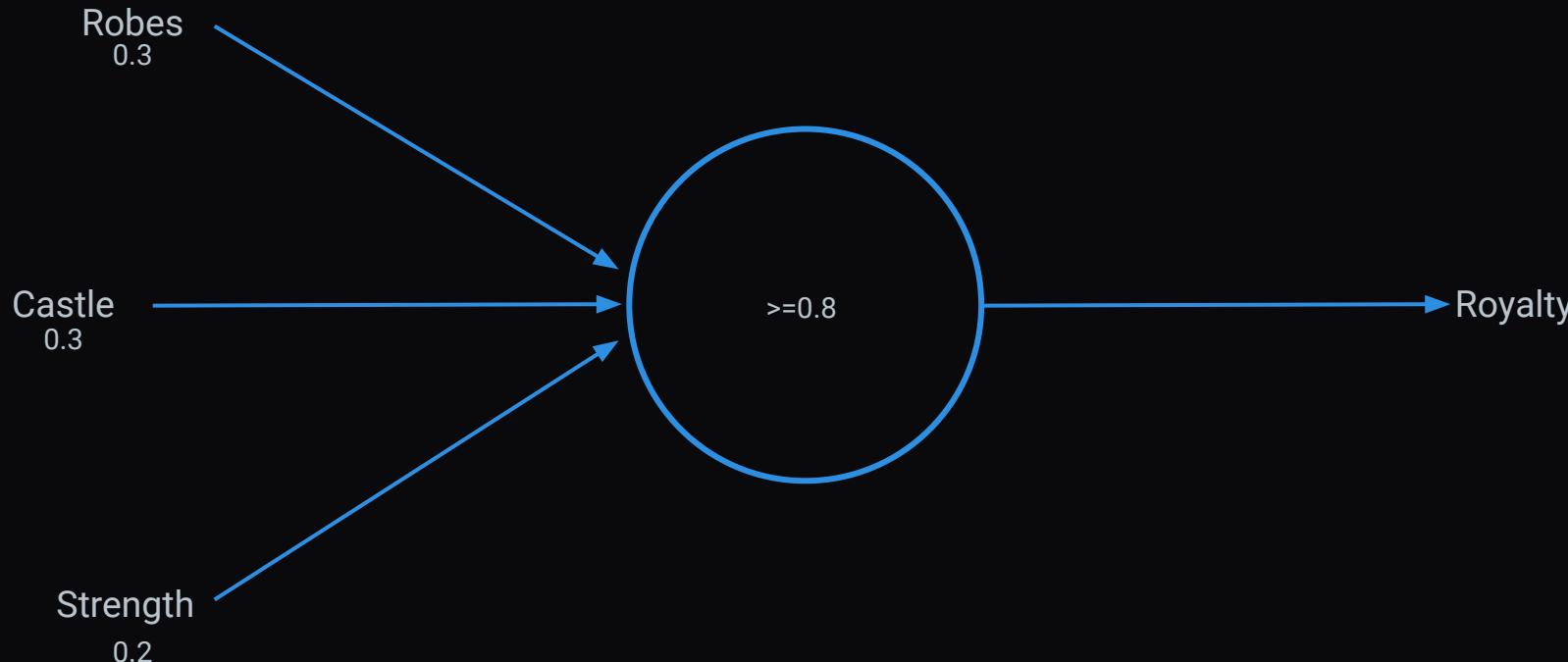
input2 = .2

input3 = .25



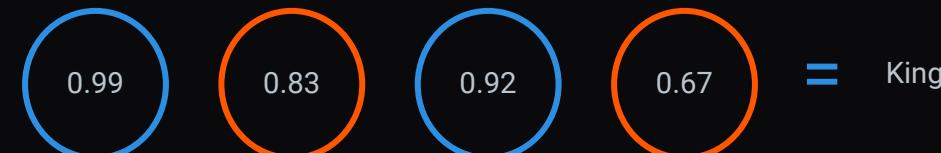


# The inputs can be the presence of nearby words



Remember like pixels, words are just a series of numeric values 0/1s.

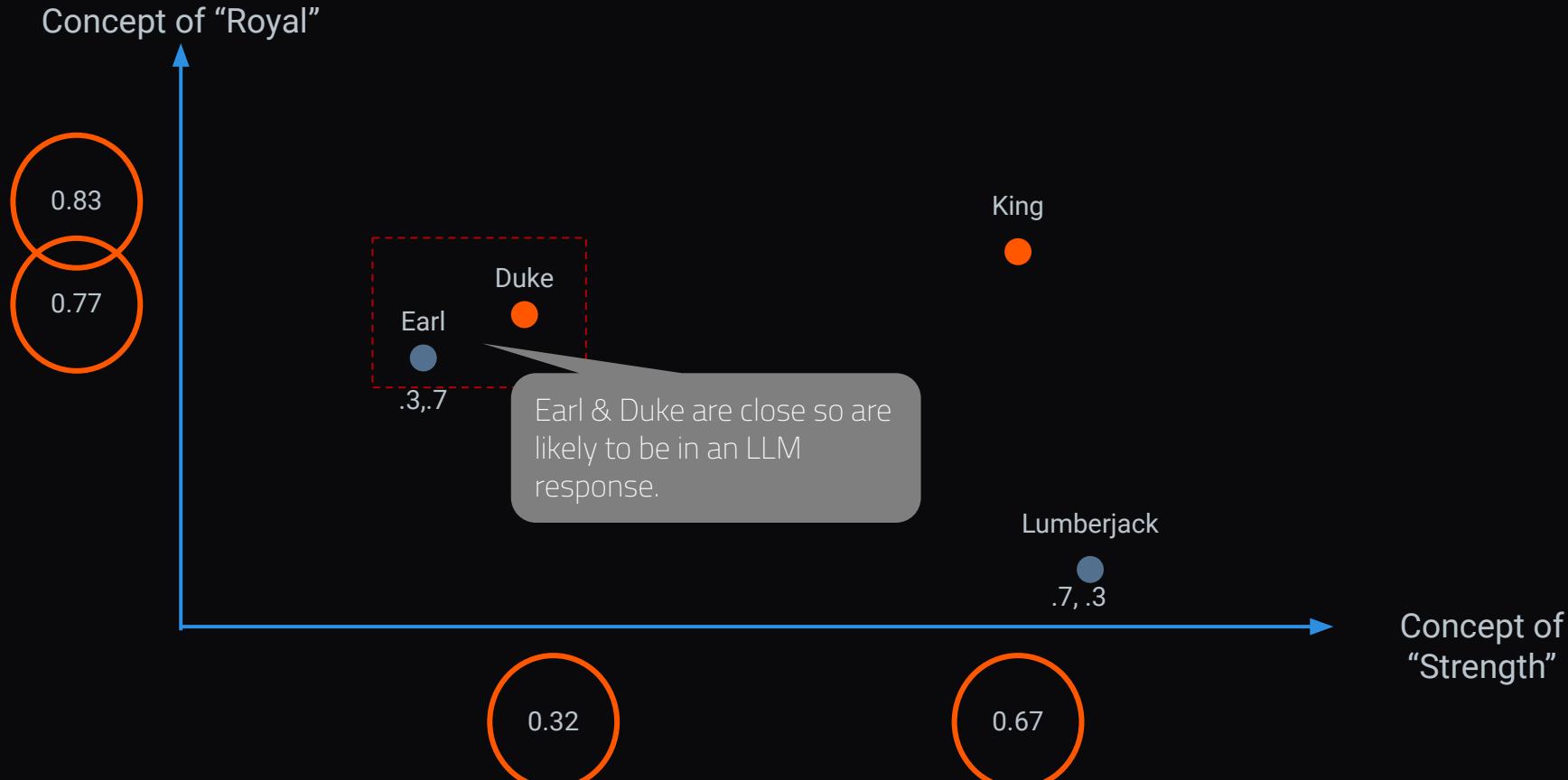
# Activations become “serial numbers” representing concepts



Concept serial numbers (called embeddings) can have 1536 values with 16 digits each.



# Words & concepts are identified in a similar region





# An LLM builds concept by concept, token by token.

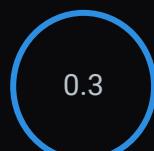
George Mason University is a



public



private

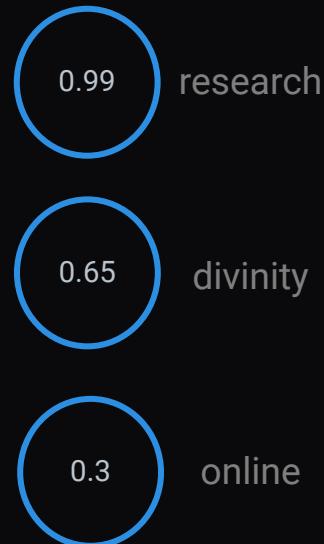


non-profit



An LLM builds concept by concept, token by token.

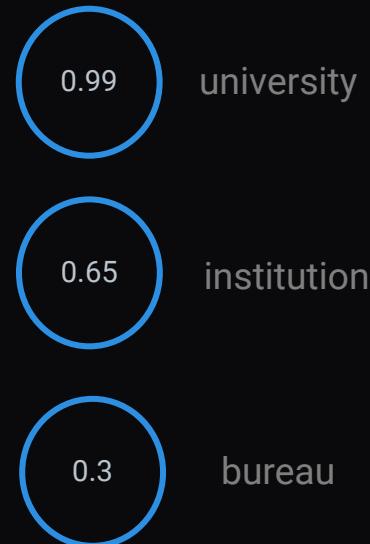
George Mason University is a **public**





An LLM builds concept by concept, token by token.

George Mason University is a public **research**



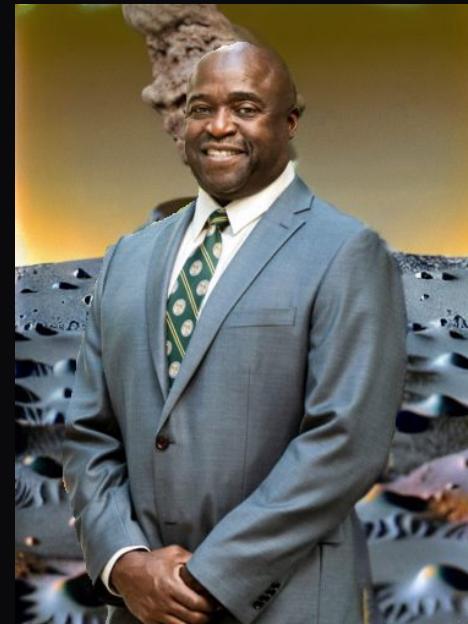


# An LLM builds concept by concept, token by token.

## Language to Language

George Mason University is a  
George Mason University is a public  
George Mason University is a public research  
George Mason University is a public research university.

## Language to Image



Stable Diffusion “inpainting”  
with midjrn-4 custom  
model, “a lunar landscape  
with craters, high definition”

LLMs reconstruct large sections of text similar to what it’s already seen i.e. Lossy Compression.  
Image generation is the same but for pixels.

# Navigating the parameters with prompts can lead to problems.



 **You**  
do you know any personnel at George Mason University such as the president?

 **ChatGPT**  
I don't have real-time information or access to databases, and my training only includes information available up to January 2022. As of my last update, **Anne Holton** was serving as the interim president of George Mason University. However, leadership positions at universities can change, so I recommend checking the official George Mason University website or contacting the university directly for the most up-to-date information on personnel, including the president.

Learning to extract the information needed from LLMs, called "Prompt Engineering" is a learned skill.



You

Who is the president of George Mason University?



ChatGPT

As of my last knowledge update in January 2022, Anne Holton was serving as the interim president of George Mason University. However, university leadership can change, and I don't have real-time information. To get the most current information on the president of George Mason University, please check the university's official website or contact the university directly.

Doubles down on Anne Holton.



You

Who is the president of George Mason University?



ChatGPT

As of my last knowledge update in January 2022, Anne Holton was serving as the interim president of George Mason University. However, university leadership can change, and I don't have real-time information. To get the most current information on the president of George Mason University, please check the university's official website or contact the university directly.



You

Who is Gregory Washington?



ChatGPT

As of my last knowledge update in January 2022, Gregory Washington was the president of George Mason University. However, keep in mind that leadership positions can change, and it's always a good idea to verify information with the latest sources. To get the most up-to-date information on Gregory Washington's role or any changes in leadership, please check the official website of George Mason University or other reliable news sources.



Unless you ask it more specific information in the same conversation. Is there an interim and regular president simultaneously?



EH

You

where was Gregory Washington born?

ChatGPT

As of my last knowledge update in January 2022, Gregory Washington was born in Florida, USA. However, keep in mind that personal details such as birthplaces are subject to change, and it's a good idea to verify this information through the latest sources or the official biographical details provided by Gregory Washington or the institution with which he is associated.

It will make plausible assertions but not really have a concept of what's being stated.



## Early life and education [edit]

Washington was born in New York City. He attended William G. Enloe High School in Raleigh, North Carolina.<sup>[2]</sup> graduating in 1984.<sup>[citation needed]</sup> Washington studied mechanical engineering at North Carolina State University. He earned his bachelor's degree in 1989 and his doctoral degree in 1994.<sup>[3]</sup> In the early 1990s he assisted in creating *The Nubian Message*, an African-American student newspaper. He was the first person in his family to obtain a university degree.<sup>[2]</sup>

The plausible assertion is called a hallucination.



You

was Gregory Washington born in Florida?



ChatGPT

As of my last knowledge update in January 2022, Gregory Washington, an American engineer and academic, was born on December 10, 1963, in St. Petersburg, Florida.

However, please note that information may have changed since then, so I recommend verifying the latest details from a reliable source to ensure accuracy.

With "born" and "Florida" the LLM was trained on a lot of documents that had dates & towns of Florida. And it still thinks this is dynamic & can change.



You

who is Tom Cruise's mother?



ChatGPT

As of my last knowledge update in January 2022, Tom Cruise's mother is Mary Lee Pfeiffer. However, it's important to note that information about individuals can change, and I may not have the latest details. I recommend checking more recent sources for the most up-to-date information on Tom Cruise's family.



A to B.



You

who is Mary Lee Pfeiffer's son?



ChatGPT

I'm sorry, but I couldn't find any information on a person named Mary Lee Pfeiffer or details about her son in my training data up to January 2022. It's possible that she may not be a public figure or that the information is not widely available. If she is a private individual, it would be inappropriate to share personal details about her or her family. If Mary Lee Pfeiffer is a public figure and there is information about her son that has become available after my last update, I recommend checking recent and reliable sources for the latest information.

B to ??

# My \$0.02 on AI



## As Educators

- Teach about the technology +/-
  - AI affects who they date, what side of an issue they learn about, what job advertisements they see
  - "AI won't replace lawyers, it will replace lawyers that don't use it"
- Showcase AI as a thought partner; students will use and be affected by AI in their daily lives
  - Use it for brainstorming, comparing/contrasting topics & concepts
  - Build upon the output with expertise/creativity
  - Learn prompting strategies
- Critical thinking, specific knowledge & creativity > rote memorization

## As Consumers

- Healthy skepticism both +/-
- Understand the impact is widespread & know when to support appropriate use; AI isn't always needed



# Agenda

- 1. The hype cycle of AI!**
- 2. What about genAI (chatGPT)?**
- 3. AI in Research**
  - a. Emerging genAI tools
  - b. Clinical Recommendations for Spinal Cord Injury Surgery (PLOS One)
  - c. Informing Government decision making for improving access to drinking water
  - d. Common challenges with AI in research

# Multiple, new genAI services for research and synthesis



Do direct cash transfers reduce poverty?

Synthesize

**Summary** beta  
Top 10 papers analyzed

These studies suggest that direct cash transfers can reduce poverty and inequality, with varying effectiveness depending on factors such as program management, progressive transfers, and regional differences.

**Consensus Meter** beta  
14 papers analyzed

Response	Percentage
Yes - 93%	93%
Possibly - 0%	0%
No - 7%	7%

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# But genAI still faces many fundamental challenges for applied AI research





## Using operating room data of SCI patients to **improve clinical guidelines**



### What UCSF accomplished

- Discovered new, critical relationship between **high BP** and **neurological outcomes**. Findings progressed for further clinical implementation



### Why it matters

- New findings inform care-standard changes at ZGH



### AI Research Challenges

- Model development with small samples (N=75) and >75 Features
- Reducing variables for the final model
- Peer review process

### Meet UCSF!



Austin  
Researcher



Adam  
PI

### Projects Created

508

### Modeling Hours

5,441

# The Numbers of Spinal Cord Injury



- ~18,000 new SCI cases each year in the US
  - ~300,000 people living with a SCI
  - < 1% of patients have complete neurological recovery when discharged from the hospital
  - > 99% of patients experience some degree of life-long paralysis.
- The average lifetime financial burden for a patient ranges from \$1 to 5 million dollars

# Challenges of Biomedical Data Science



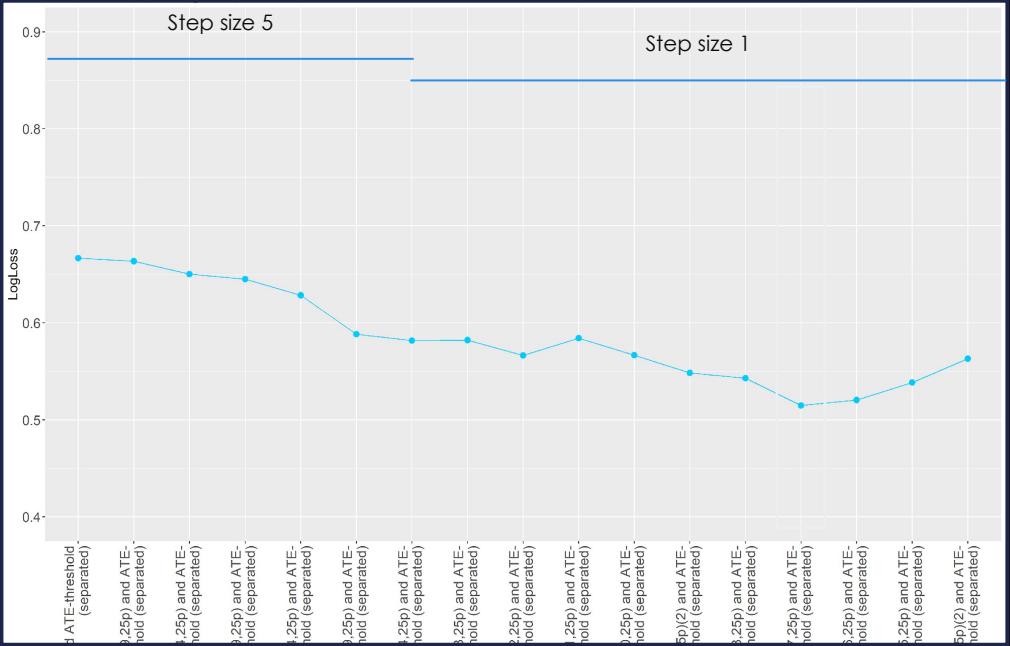
- **Small but wide dataset ( $n=75$ ,  $D>100$ )**
- **Data collected at different points in patient journey**
- **Characterizing model precision and stability**
- **Interpreting the model and communicating findings**

## Example Data Types

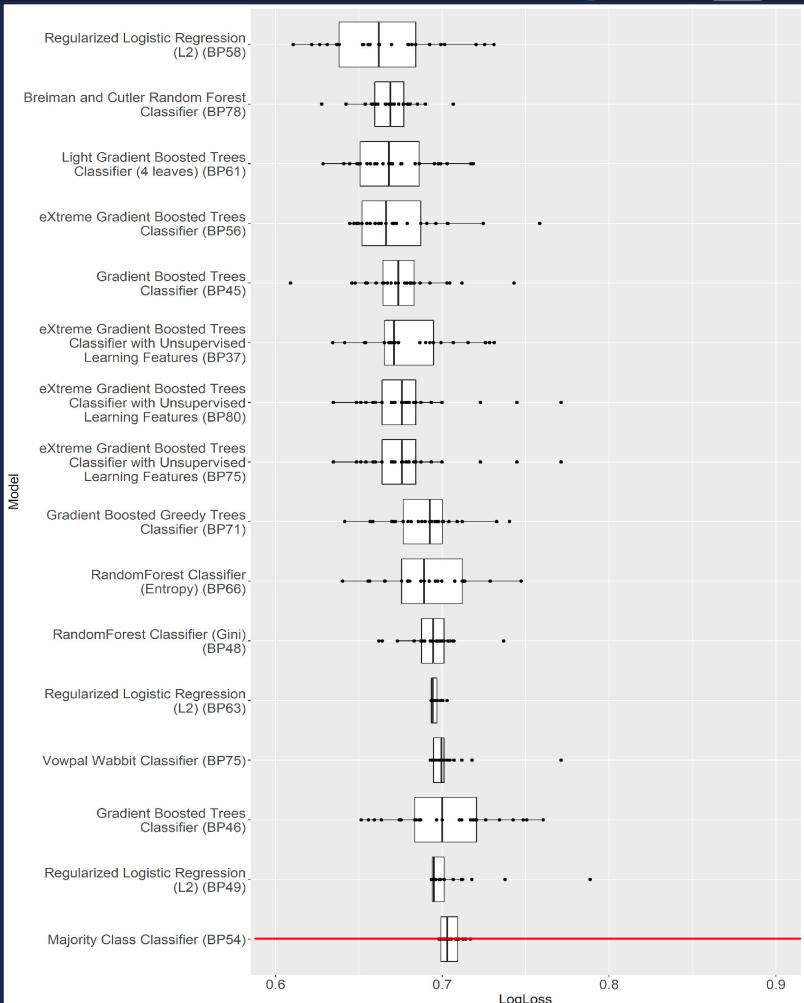
- High-frequency physiology data
- Clinical outcome exams
- Surgical procedures
- ICU medications
- Imaging parameters
- Blood-based biomarkers

# Selecting the final model for publication

Which variables to include? Expert guided variable reduction improved performance



Accuracy differences across algorithms





## Predicting the **functional status** of waterpoints across 15 African countries



### What GWC accomplished

- Developed models to predict if a water point will fail today and in 2 years, for 15 countries.
- Transparent documentation of models to stakeholders



### Why it matters

- Enabled creation of a data platform to inform government resourcing decisions for water point repairs and new construction
- Delivered trainings to gov't in Sierra Leone, Liberia, Uganda, Kenya



### AI Research Challenges

- Large, messy, crowd-sourced data of image, text, tabular data
- Irregular time intervals of data collection
- Multiple 3rd party data sets to augment data
- Unique implementation challenges per government

### Meet GWC and Akvo!

**Katy****Lars**

Director, GWC Consultant, Akvo



**Global Water Challenge (GWC)** supports investment in Water, Sanitation and Hygiene (WASH) in developing nations, particularly rural water points like handpumps



**In Sierra Leone, 2 million people depend on daily water from ~28k rural water points.** However, 25% break after 4 years and resources for construction, maintenance and repair are scarce.



**GWC developed models to predict which waterpoints will break in the future.** The model is deployed in Sierra Leone and is required for use by the government to plan new construction or repairs, and to create local budgets. 8 new countries began adoption since 2022.

# Challenges in Rural Water Development



Credit: CJTF-HOA

# A Mountain of Messy Data → 800k standardized data points

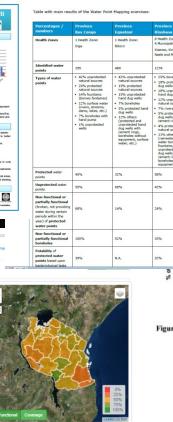


Table 20

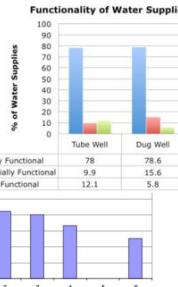
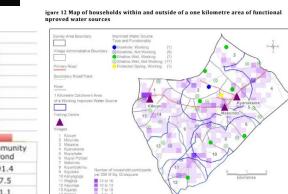


Figure 2: Percentage of Non-Functioning Boreholes per Ward as of April 2010

37th WEDC International Conference, Hano

SUSTAINABLE WATER AND SANITATION  
FOR ALL IN A FAST CHANGING WORLD

## **Assessment of the functionality of hand drilled through the Basic Services Function**



Source: A Social-Spatial survey of Water Issues in Makondo Parish, Uganda (Macri et al., 2010).



The total number of



### 3.1.4 Technical Functionality

When a system is classified as **'fully functioning'** it implies that the entire system is functioning as it was planned to. For the purposes of technical surveying, the full functionality of a system may have been demoted and reclassified to **'partly functioning'** where at least one component of that system is no longer functioning adequately, such that it significantly hinders sustainability, water quality or effective o&m. A **'non-functioning system'** is one that cannot deliver water due to technical factors.

Table 11: Technical functionality s

Is the system installed technically functioning? (does it deliver water to the people?)	
Fully	41 (41.00%)
Partly	45 (45.00%)
Not Functioning	14 (14.00%)



## Functionality status of Rural Water Supply Schemes



# ML Challenge: Data from many locations at different times



Sierra Leone

x Bo x Kailahun x Port Loko

Select a Sub-District

Last Known Status

Select a Water Source

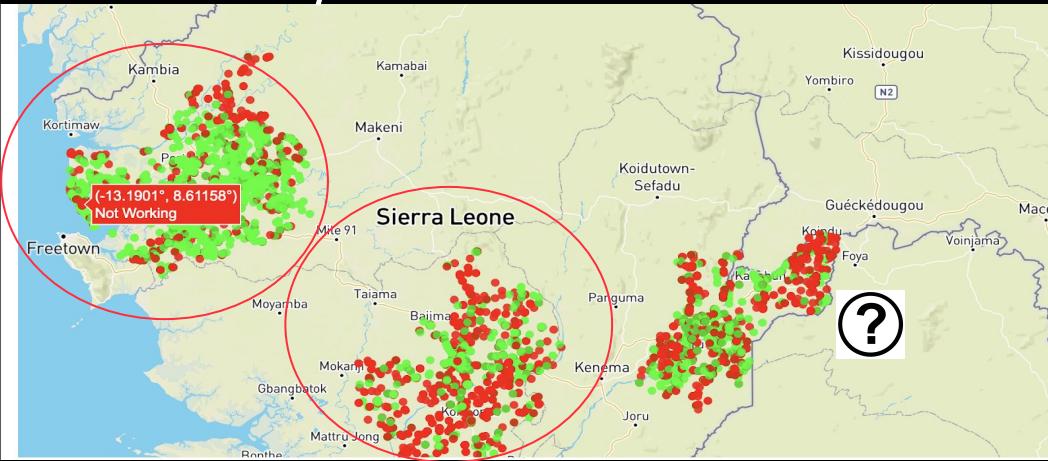
x Afridev x India Mark MK IMK II

Select Water Point Management

Select Today's Prediction

Not Working

Working





# Validating a model across time

Factors regarding water points change over time. Model validation & holdout partitions are set up accordingly using out of time validation (OOTV)

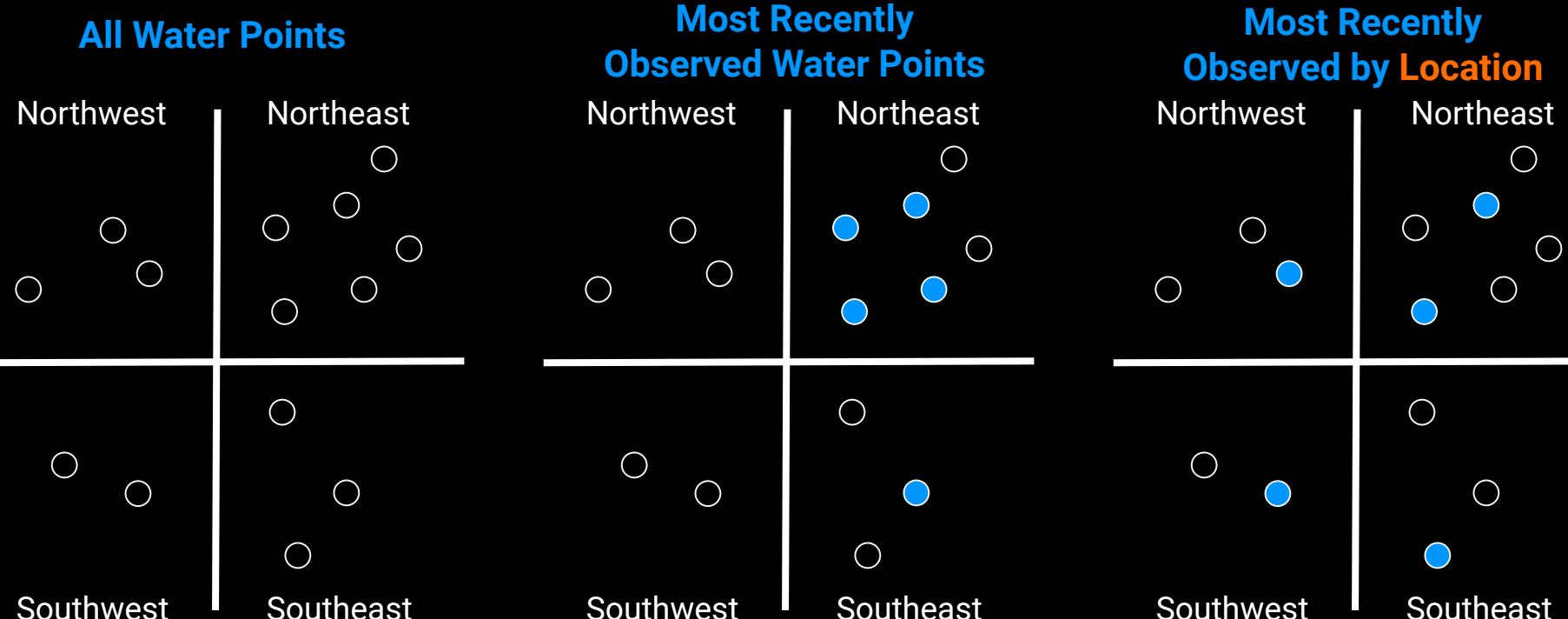
Problem	Solution
<b>Holdout set should be as representative of the real world as possible</b>	Use the most recent 20% of observations as holdout set to ensure it is as similar to future data as possible
<b>Cross validation should never test future data on past data</b>	Use OOTV (out of time validation) to ensure validation set is always future data as is true in practice



# Validating a model across space



Partitioning with respect to a coordinate space maintains geographic distributions



# Validating a model across time & space

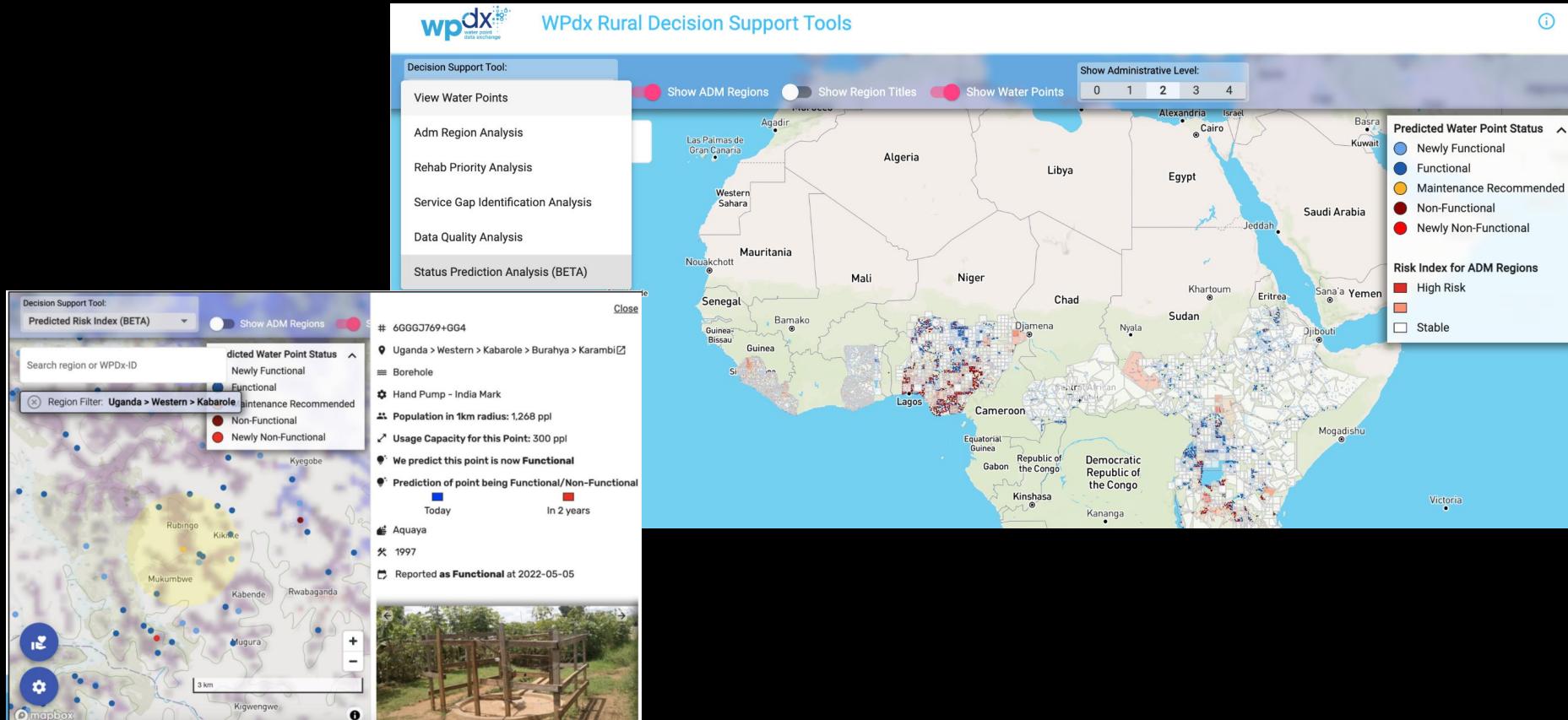


When partitioning across time & space, **observations across segmented spaces are partitioned together by how recently they were measured relative to other observations in their space.**

Outcomes:

- The **holdout set is 20% of the most recent observations of water points in a given area** that fairly represents water points from an entire country
- Validation accuracy **predictions are not being biased by use of future data** not known at time of measurement
- Higher confidence the model will **generalize to new countries and regions**

# Policy and government data for AI is often a mess. Upfront data work is needed to build useful tools



# Common themes for challenges in research



- Problem framing for ML and data strategy
  - Evaluating multiple models and validating their results
  - Interpretation of variable importance, direction at the model, and record, level
- Conviction in results to influence change for high-impact use cases

# AI is often an interdisciplinary project requiring communication, qualitative, specific subject & technical expertise.



Planning & Strategy



Data Fluency



Build & Validate a Model



Deploy the Technology



Continuous Monitoring



Project Mgrs



Business Operations



Business Analysts



Data Engineers



Data Scientists



Software Developers



Dev Ops



IT



Business Users



Stakeholders



Risk and Compliance

## AI INNOVATORS

Liberal arts, business, communication/English & specialty knowledge i.e. healthcare

## AI CREATORS

Analytics, math

## AI OPERATORS

Computer science

## AI CONSUMERS

Ethics/Governance, English/Communication

# There is no automated solution for problem identification, framing, data collection and implementation strategy



 Discovery & Problem Definition

 Data Preparation & Feature Engineering

 Model Development

 Model Validation & Evaluation

 Deployment & Integration

 Monitor, Audit & Retrain

Researcher A

Understanding The Business Problem  
ML Problem Framing  
Data Feasibility  
Anticipated Use / Adoptability

Anticipated ROI  
Prioritization

Find & Access Dataset  
Database Integration  
Exploration  
Cleansing  
Merging and Joining

Transformation  
Aggregation  
Governance - Data Change Log  
Scheduled & Auditable Workflows

Feature Engineering  
Feature Discovery and Interactions  
Feature Transformation  
Out-of-sample Testing / Back Testing

Model Leaderboard  
Hyper-parameter Tuning  
Notebook Pipelines & API Accessibility  
Model Selection

Evaluation of Results  
Model & Observation-Level Explainability  
Feature Importance  
Bias Assessment

Profit Curve  
Internal And External Model Validation  
Compliance Documentation  
Model Validation

Deploy Anywhere  
Central Model Registry  
Model Versioning  
Approval Workflows  
Audit & Compliance Reports

- Service Health Monitoring
- Data Drift
- Accuracy Tracking
- Champion/ Challenger
- Hot Swap Models
- Prediction Explanations
- Bias Detection
- Prediction History

Researcher B

\* Applies to both supervised and unsupervised models including time series

Student

 Fully Automatable

 Some Automation + Human Input/Oversight

 Can be Pipelined  
Human-in-the-loop/ Domain Expertise is Vital

# Tool: Establish a common language to evaluate AI research ideas

## 01 Use case Qualification

- Is it a Machine learning problem ?
- Does it have a quantifiable business value you can measure?
- ▶ Does it have a strategic value ?
- How will the business process change? Is it worth it?
- Are the stakeholders and resources aligned ?

## 02 Technical Qualification

- Is the data readily available ?
- ▶ Can the scoring data and model be implemented ?
- How will you validate and select your model? Share insights?

## 03 Setting up

- ▶ Add info to Use case Tracker and share with all the stakeholders

## 04 Final Check-in

- Data is in the right form
- ▶ Data preparation is done
- Deployment end-point identified and primed

## 05 Build

- ▶ Sprint session to kick off use-cases for 2-3 weeks
- Periodic check-ins w/Business stakeholders / SMEs

## 06 Productionalize / Publish

- ▶ Incorporate decision intelligence flows pre-deployment
- Productionize models

## 07 Continuous AI

- ▶ Monitoring of models and refreshing of models in production
- Business stakeholder impact and drift reasons read-out

## Before the kick off:

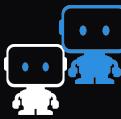
- Use case tracker is updated with all the info
- Effort to ROI impact alignment
- Deployment path cleared
- Timelines committed w/regular updates

# So many algorithms, which to use? Leverage automation



% out of 165 datasets where model A outperformed model B														
Wins	GTB	RF	SVM	ERF	SGD	KNN	DT	AB	LR	PA	BNB	GNB	MNB	Losses
	Gradient Tree Boosting -	32%	45%	38%	67%	72%	78%	76%	78%	82%	90%	95%	95%	
	Random Forest -	9%		33%	23%	62%	65%	71%	69%	71%	76%	85%	95%	90%
	Support Vector Machine -	12%	21%		25%	55%	65%	56%	62%	67%	74%	79%	95%	93%
	Extra Random Forest -	8%	14%	30%		58%	63%	61%	64%	67%	70%	81%	93%	91%
	Linear Model trained via Stochastic Gradient Descent -	8%	16%	9%	15%		38%	41%	44%	41%	61%	66%	89%	87%
	K-Nearest Neighbors -	4%	8%	7%	8%	35%		42%	45%	52%	53%	70%	88%	85%
	Decision Tree -	2%	2%	20%	8%	42%	38%		43%	48%	57%	69%	80%	82%
	AdaBoost -	1%	7%	10%	15%	30%	35%	32%		39%	47%	59%	76%	77%
	Logistic Regression -	5%	10%	3%	8%	11%	31%	33%	35%		37%	54%	79%	81%
	Passive Aggressive -	2%	6%	1%	5%	0%	18%	28%	28%	13%		50%	81%	79%
	Bernoulli Naive Bayes -	0%	2%	2%	4%	10%	13%	18%	15%	22%	25%		62%	68%
	Gaussian Naive Bayes -	0%	1%	3%	2%	6%	6%	11%	12%	9%	10%	22%		45%
	Multinomial Naive Bayes -	1%	1%	2%	2%	2%	5%	10%	14%	4%	5%	13%		39%

Source: [Olson 2018](#)  
[Penn ML Benchmarks](#)



# Evaluation: Model Agnostic Explanation Tools

**What are features driving the model?** Permutation importance

**How is a specific feature driving?** Partial dependence

**Let's explain some examples?** Shapley values





# Research of Consequence

## Major Themes and Statements



### Broad impact and contribution to society

Contributes to the larger community, addressing issues at various levels, from the local community to the nation and beyond. This research is designed to have a broad impact and provide valuable insights to solve problems that affect society as a whole



### Influence on practice and policy

Directly informs or impacts practice and policy. It is scholarship that leads to tangible changes in the way things are done, whether in educational, health, sports, recreation, and tourism contexts, or the broader society. The goal is to improve the effectiveness of practices and policies.



### Real world application and dissemination

Produces research findings that reach the people who can immediately benefit from them. Research of consequence is not limited to theoretical discussions but actively engages with real-world problems, disseminating applicable knowledge and solutions to various contexts.



### Positive difference and improving lives

Makes a positive difference in the lives of individuals and communities, both locally and globally. It goes beyond just being an academic exercise and focuses on improving the well-being and experiences of people, particularly students, families, and marginalized communities.

# Summary



ML models can learn highly nonlinear, complex relationships from predictors and an outcome

Highly varied data types can be added and are often useful : Images, text, audio, etc

How this data is aggregated can be problematic; observational/open source, hidden/ implicit bias

Validating results is nuanced, how you set up data matters, particularly in health. Small wide, big / messy

Interpretation for policy level influence can be challenging. Many tools: Algo, model agnostic, local, global

**Deployment to be useful to policy / people is hard.** Many landmines to get to recommending actions





# Questions?



# Backup



NEWS | 29 August 2018

# Artificial intelligence nails predictions of earthquake aftershocks

A neural-network analysis outperforms the method scientists typically use to work out where these tremors will strike.

By [Alexandra Witze](#)



A machine-learning study that analysed hundreds of thousands of earthquakes beat the standard method at predicting the location of aftershocks.



Dear Editors:

A recent paper you published by DeVries, et al., *Deep learning of aftershock patterns following large Earthquakes*, contains significant methodological errors that undermine its conclusion. These errors should be highlighted, as data science is still an emerging field that hasn't yet matured to the rigor of other fields. Additionally, not correcting the published results will stymie research in the area, as it will not be possible for others to match or improve upon the results. We have contacted the author and shared with them the problems around data leakage, learning curves, and model choice. They have not yet responded back.

First, the results published in the paper, AUC of 0.849, are inflated because of target leakage. The approach in the paper used part of an earthquake to train the model, which then was used again to test the model. This form of target leakage can lead to inflated results in machine learning. To prevent against this, a technique called group partitioning is used. This requires ensuring an earthquake appears either



These comments were made without any scientific context. We are earthquake scientists and our goal was to use a machine learning approach to gain some insight into aftershock location patterns. We accomplished this goal. The authors of these comments do not – we will be disappointed if *Nature* publishes them.

Phoebe DeVries and Brendan Meade

To summarize: regarding point (1), I wish the Devries et al. study had controlled for potential data leakage, but do not feel that the main results of the paper are compromised by doing so. As for point (2), I think it is interesting (though not surprising) that the neural network



# A Deeper Look into ‘Deep Learning of Aftershock Patterns Following Large Earthquakes’: Illustrating First Principles in Neural Network Physical Interpretability

Arnaud Mignan & Marco Broccardo

Conference paper | [First Online: 16 May 2019](#)

3211 Accesses | 3 Citations | 10 Altmetric

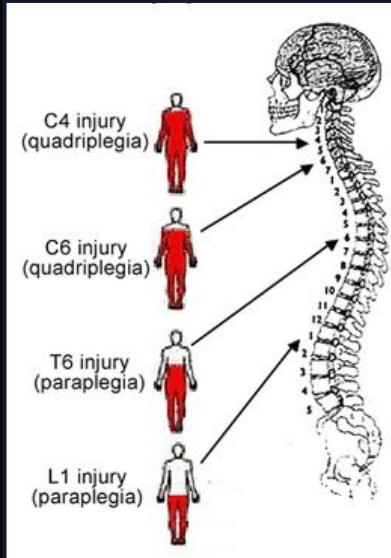
Part of the [Lecture Notes in Computer Science](#) book series (LNTCS, volume 11506)

## Abstract

In the last years, deep learning has solved seemingly intractable problems, boosting the hope to find (approximate) solutions to problems that now are considered unsolvable. Earthquake prediction - a recognized moonshot challenge - is obviously worthwhile exploring with deep learning. Although encouraging results have been obtained recently, deep neural networks (DNN) may sometimes create the illusion that patterns hidden in data are complex when this is not necessarily the case. We investigate the results of De Vries et al. [*Nature*, vol. 560, 2018] who defined a DNN of 6 hidden layers with 50 nodes each, and with an input layer of 12 stress features, to predict aftershock patterns in space. The performance of their DNN was assessed using ROC with  $AUC=0.85$  obtained. We first show that a simple artificial neural network (ANN) of 1 hidden layer yields a similar performance, suggesting that aftershock patterns are not necessarily highly abstract objects. Following first principle guidance, we then bypass the elastic stress change tensor computation, making profit of the tensorial nature of neural networks.  $AUC=0.85$  is again reached with an ANN, now with only two geometric and kinematic features. Not only seems deep learning to be “excessive” in the present case, the simpler ANN streamlines the process of aftershock forecasting, limits model bias, and provides better insights into aftershock physics and possible model improvement. Complexification is a controversial trend in all of Science and first principles should be applied wherever possible to gain physical interpretations of neural networks.



"If you've recently experienced a spinal cord injury, it might seem like every aspect of your life has been affected. You might feel the effects of your injury mentally, emotionally and socially." (Mayo Clinic)

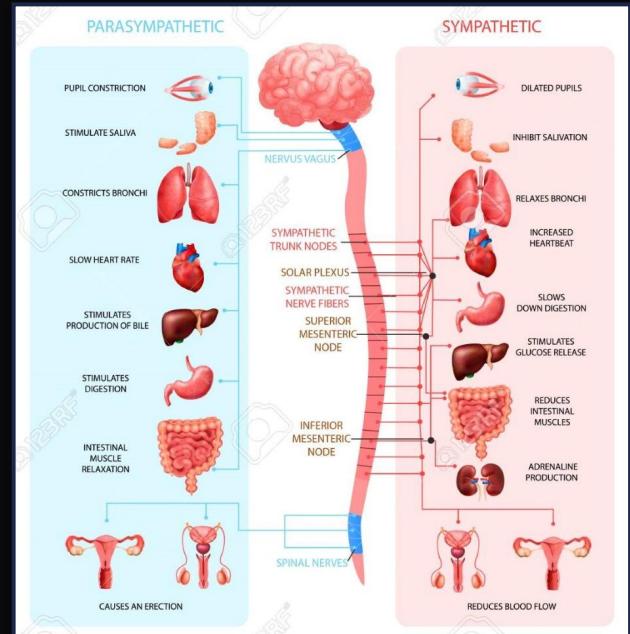


### • Autonomic Symptoms

- Cardiovascular and circulatory
- Respiratory
- Gastrointestinal
- Bowel and bladder function
- Sexual functions

### • Chronic Pain

- Anxiety/Depression
- Cognitive Impairment





# TRACK-SCI Team



Data Science  
Abel Torres Espin, PhD



Data Science (Basic/Clinical)  
Adam R. Ferguson, PhD



SCI Science (Basic, Clinical)  
Jacqueline Bresnahan, PhD



SCI Science (Basic/Clinical)  
Michael Beattie, PhD



Neurosurgery  
Sanjay Dhall, MD



Neurosurgery  
Geoffrey Manley,  
MD PhD



Neuroradiology  
Jason Talbott,  
MD PhD



Emergency Medicine  
William Whetstone, MD



Data Science  
Austin Chou, PhD



Neurology/Critical Care  
Vineeta Singh, MD



Multi-omics  
J. Russell Huie, PhD



Transcriptomics  
Nikolaos Kyritsis, PhD



ICU Critical Care  
Debra Hemmerle, RN



PM&R  
Lisa Pascual, MD



Research Coordination  
Xuân Dương Fernández, BA  
Leigh Thomas, BA  
Sara Moncivais, MA



Anesthesiology  
Jonathan Pan, MD  
PhD



Neurosurgery  
John Burke, MD, PhD



Neurosurgery  
Anthony DiGiorgio,  
MD

**Themes - problem framing, managing small and large data with ML, interpretability, b&F**  
**Lots of algorithms, lots of interpretability approaches, lots of data with lots of bias, lots of ways to use a predictive model to inform policy or influence action**  
**All challenges students and researchers will face, and continue to face.**



If time- point out that referees dont seem to have consistent views. 2018, and 2023

### **Supporting research of consequence. Important skills for researchers**

- **Problem selection and framing**
  - Teach students how to identify and solve valuable problems with actionable outcomes
- **Data acquisition, manipulation, bias and fairness**
  - Leverage growing public data, with awareness of bias landmines. Teach tools for data collection
- **Leveraging AI to inform policy and community outcomes**
  - To influence policy, students must be familiar with interpreting model performance, important features, local importance, limitations, differences between RCT
  - Model evaluation and interpretability

# Bringing Order to the Data



## Water Point Data Exchange

### Standardized Hashtags

These fields are required:

• **Latitude (#lat\_deg)**

Description: Provide the decimal value of the latitude in WGS 1984. At least four decimals should be included. North and East should be noted as positive numbers.

Format: Numbers only, such as 44.4758

• **Longitude (#lon\_deg)**

Description: Provide the decimal value of the longitude in WGS 1984. At least four decimals should be included. North and East should be noted as positive numbers.

Format: Numbers only, such as 73.2119

• **Presence of Water when Assessed (#status\_id)**

Description: Identify if any water is available on the day of the visit, recognizing that it may be a limited flow.

Format: List, values can include "Yes", "No", "Unknown"

• **Date of Data Inventory (#report\_date)**

Description: Provide the date that the data was collected using ISO 8601. Time and time zone designator are optional.

Format: YYYY-MM-DD (2015-08-23) or HH:MM:SS+Timezone offset (2015-11-04T13:51:00-04)

• **Data Source (#source)**

Description: Provide the name of the organization collecting the data record.

Format: Open Text

• **Country (#country\_id)**

Description: Select the ISO two letter country classification code, selected from a list of all ISO country codes.

Format: Two letters (i.e. LR)

#### At least one of these fields is required:

• **Water Source (#water\_source)**

Description: Describe the water source (e.g. shallow well, spring, borehole, river, pond, etc.).

Format: Open Text

• **Water Point Technology (#water\_tech)**

Description: Describe the system being used to transport the water from the source to the point of collection (e.g. Afridew, gravity scheme, Mafida, India Mark II, gravity scheme, etc.).

Format: Open Text

#### These fields are optional:

• **Primary Administrative Division (#adm1)**

Description: Provide the name of the primary administrative division. The correct unit can be found at <http://www.statsatid.com>. This corresponds to "First Order" and "First Level" administrative units at <http://geonames.org> and <http://www.gadm.org> respectively.

Format: Open Text

• **Secondary Administrative Division (#adm2)**

Description: Provide the name of the secondary administrative division. The correct unit can be found at <http://www.statsatid.com>. This corresponds to "Second Order" and "Second Level" administrative units at <http://geonames.org> and <http://www.gadm.org> respectively.

Format: Open Text

• **Water Point ID (#activity\_id)**

Description: Provide the Unique ID for the specific water point infrastructure, as reported by data collector. This could be a physical ID on the water point or an internal system ID.

Format: Open Text

• **Installation Year (#install\_year)**

Description: Provide the 4-digit installation year.

Format: Four numbers (ex. 1994)

• **Structure de gestion (#management)**

Description: Select the classification of the entity that directly manages the water point. Format: List, values can include "Direct government operation", "Private Operator/Delegated Management", "Community Management", "Institutional Management", "Other".

• **Payment for Water (#pay)**

Description: Provide the payment amount and basis (e.g. monthly, per jerry can, when broken, etc.). If no amount is provided, the basis can be provided alone. An amount without a payment basis cannot be included.

Format: Open Text. If an amount is included, it should include the currency using ISO 4217 code.

• **Installer (#installer)**

Description: Provide the name of the entity or entities that installed the water system. This should be the entities that completed or was directly responsible for the construction, rather than a donor or other involved stakeholder. If a system is rehabilitated, both the initial installer and rehabilitation entity can be listed if data is available.

Format: Open Text, with multiple entities separated with a ",".

• **Condition (#status)**

Description: Provide any descriptive status regarding the condition of the water point.

Format: Open Text

• **Public Data Source URL (#orig\_link)**

Description: Provide the public link to the data record for a specific water point or full data set, including any non-standard compliant data.

Format: URL of dataset or record, starting with http://

• **Photograph (#photo\_link)**

Description: Provide the URL of a photograph of the water system. Multiple URLs can be included, with each URL separated by a comma.

Format: URL of Photograph, starting with "http://"

• **Converted Fields (#converted)**

Description: List of all fields converted by WPO from original data source.

Format: Hashtags (including #), with multiple hashtags separated by a comma