CHA Division on Addiction
Cambridge Health Alliance
HARVARD MEDICAL SCHOOL TEACHING HOSPITAL

What’s the Deal with AI and Gambling?
Hype, Reality, and Where We’re Headed

Sarah E Nelson, PhD
March 5th, 2025

Gambling Addiction: Trends in Treatment, Public Health, and Gambling
Sponsored by Sandia Resort & Casino and ICRG

Sources of Support

- DraftKings, Inc.
- Entain LLC
- The National Institutes of Health
- The Foundation for Advancing Alcohol Responsibility (FAAR)

Inputs

Magic

Output

AI & Algorithms

Input

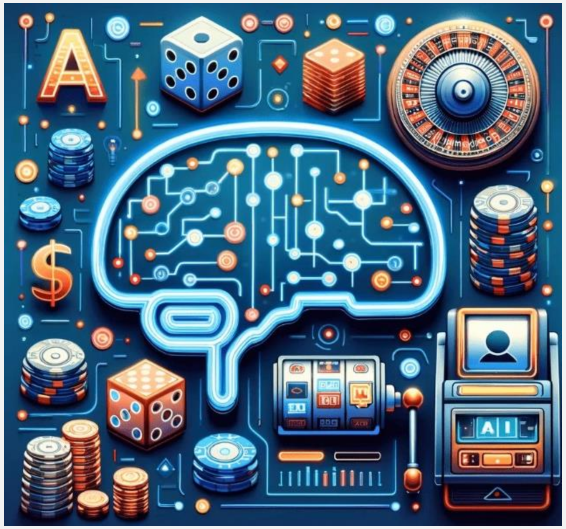
Output

- Linear Models
- Decision Trees
- Bayesian Models
- Neural Nets
- Paul the Psychic Octopus

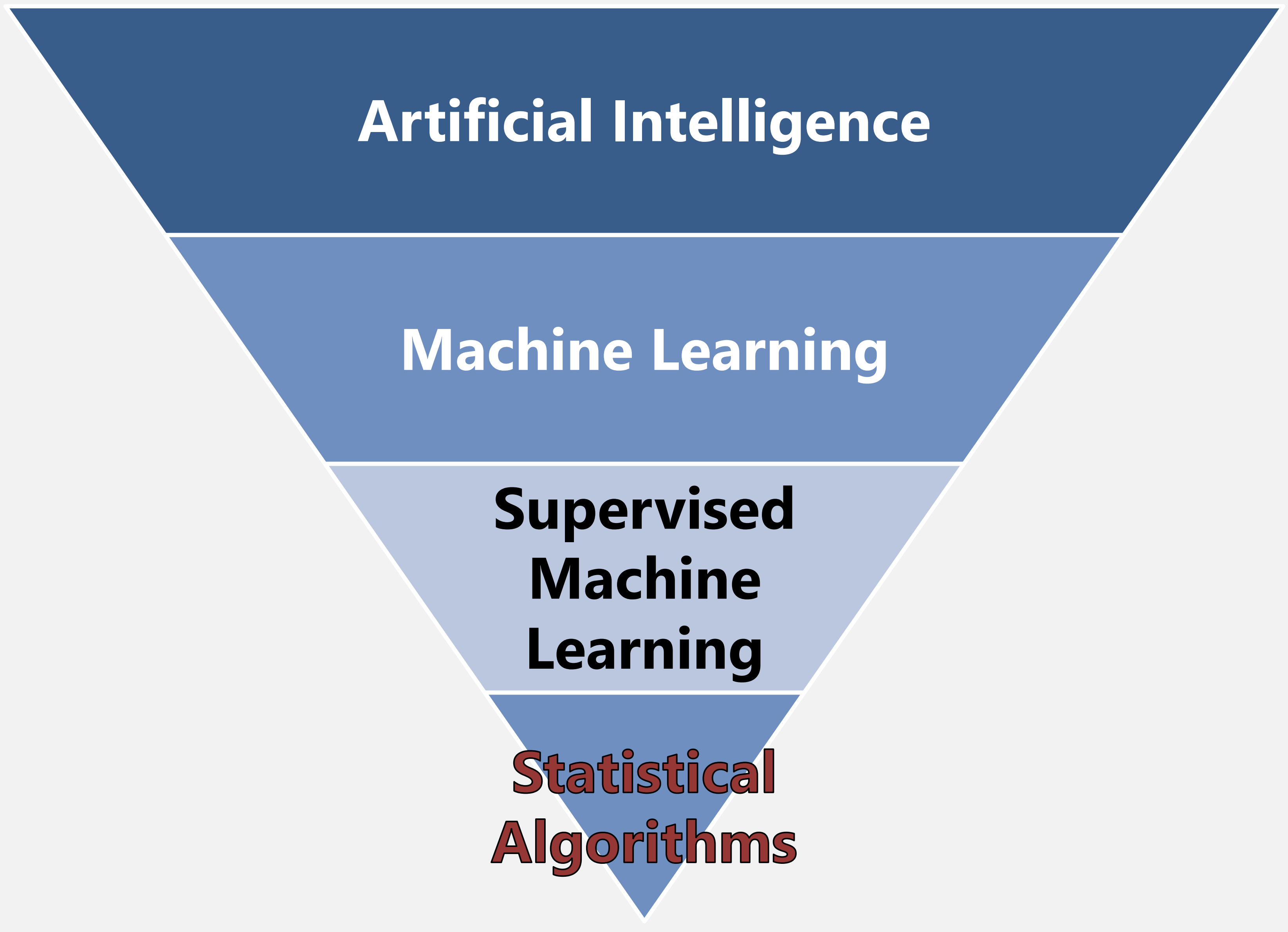
- *"The government are very keen on amassing statistics. They collect them, add them, raise them to the nth power, take the cube root and prepare wonderful diagrams. But… [it all comes down to].. the village watchman, who just puts down what he damn pleases."* – Josiah Stamp (first director of the Bank of England)

Agenda

- What is AI – defining our terms
- AI building blocks
- AI and gambling
- Problems and potential

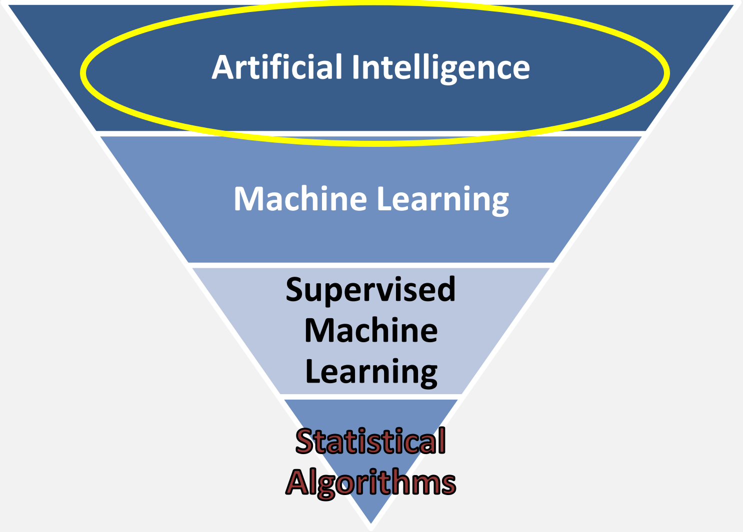


WHAT IS AI?


Artificial Intelligence
Machine Learning
Supervised Machine Learning
Statistical Algorithms

Artificial Intelligence

"…is a field of research in computer science that develops and studies methods and software that enable machines to perceive their environment and uses learning and intelligence to take actions that maximize their chances of achieving defined goals." - *Wikipedia*



Types of Artificial Intelligence

Techniques

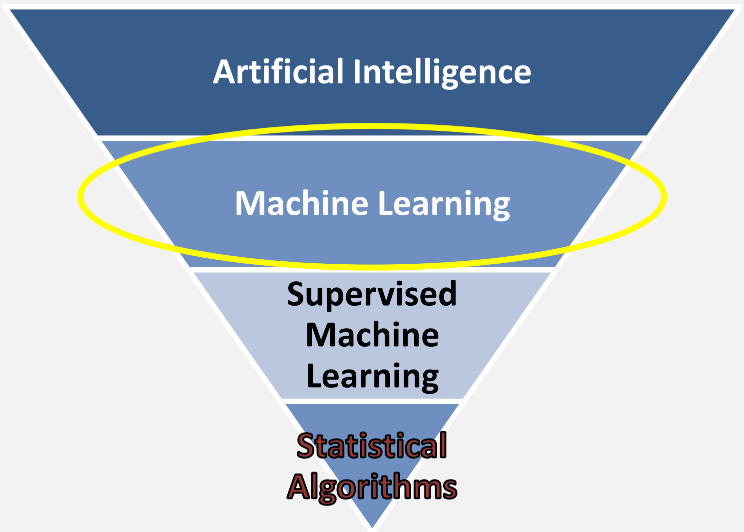
- Machine Learning
- Deep Learning
- Natural Language Processing
- Computer Vision

Purpose

- Generative
- Predictive

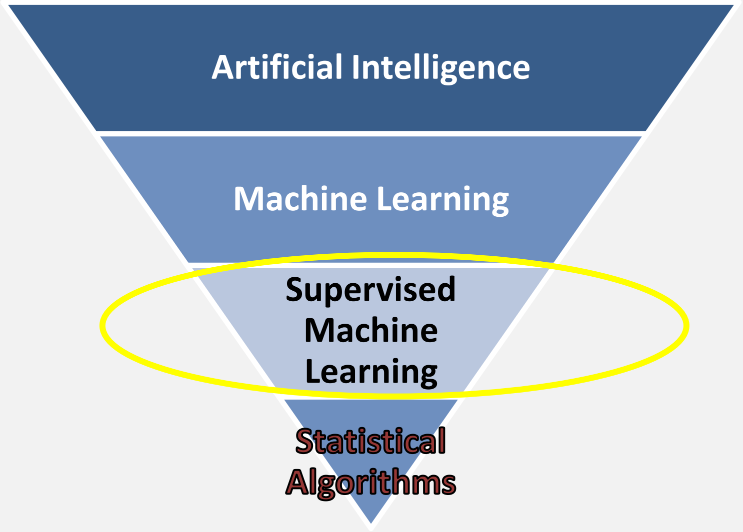
Machine Learning

"Machine learning is a field of study in artificial intelligence concerned with the development and study of statistical algorithms that can learn from data and generalize to unseen data, and thus perform tasks without explicit instructions."
-Wikipedia



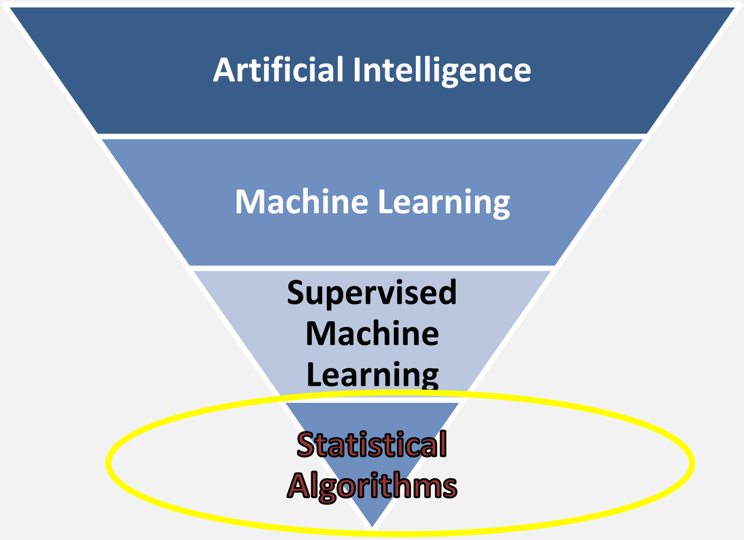
Supervised vs. Unsupervised Machine Learning

- Unsupervised ML is just trying to group cases according to patterns – no real y variable or prediction
- Supervised ML has information about what the actual outcomes are and is trying to fit a model to those.

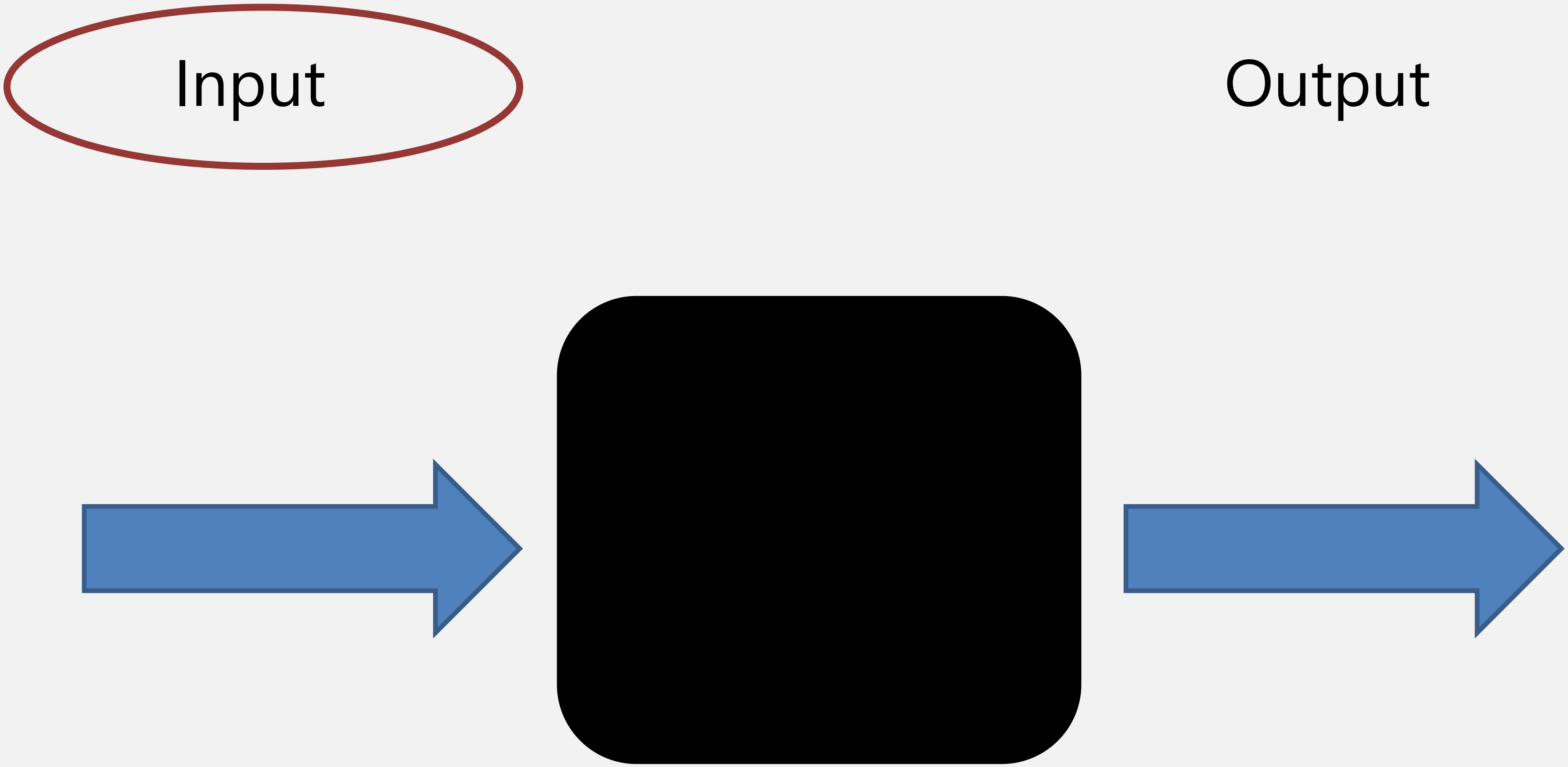


Algorithm

"…an algorithm is a finite sequence of mathematically rigorous instructions, typically used to solve a class of specific problems or to perform a computation."
- *Wikipedia*

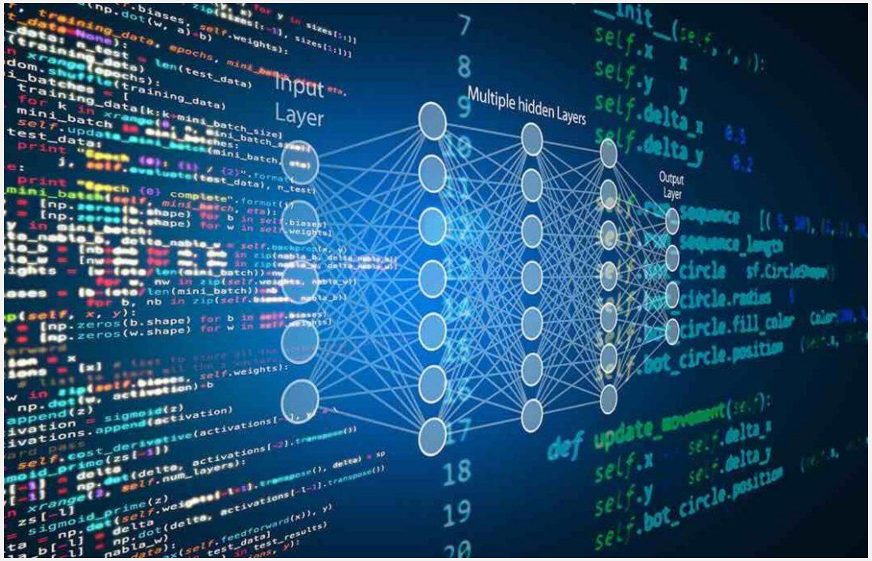


AI BUILDING BLOCKS


Input
Output

Inputs

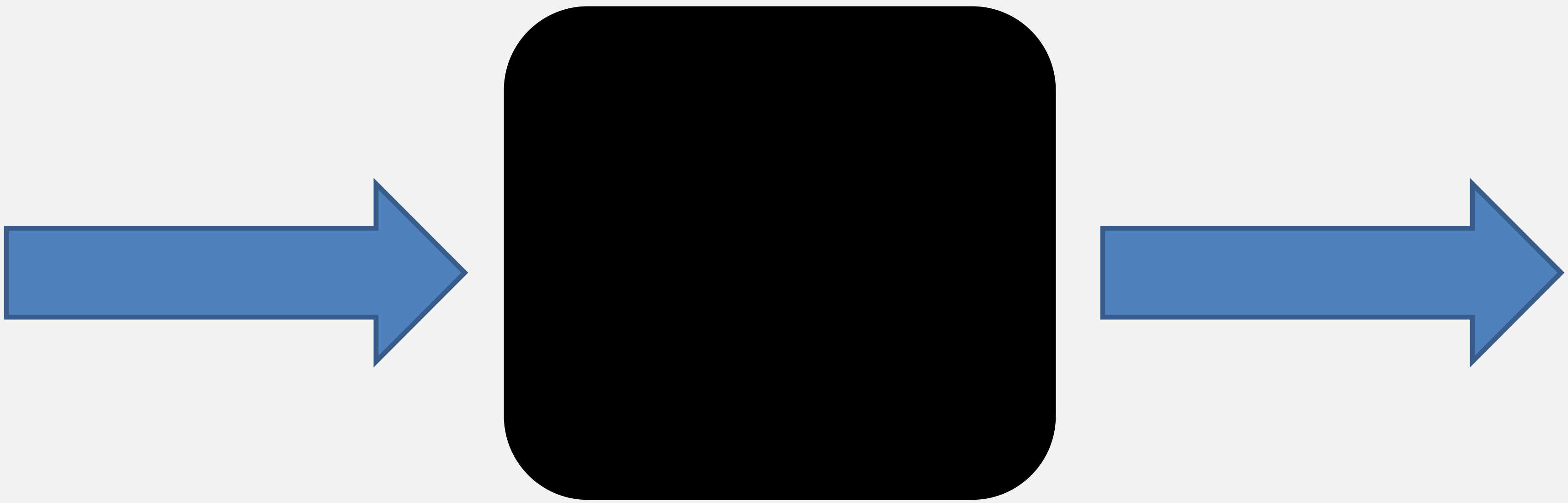
- Training data
- Could be a set of predictors we think are related to the outcome
- Could be a huge dataset with all possible predictors
- Training data specifies correct outputs – the algorithm learns from the training data and then applies its model to new data.



(Lee et al., 2024)

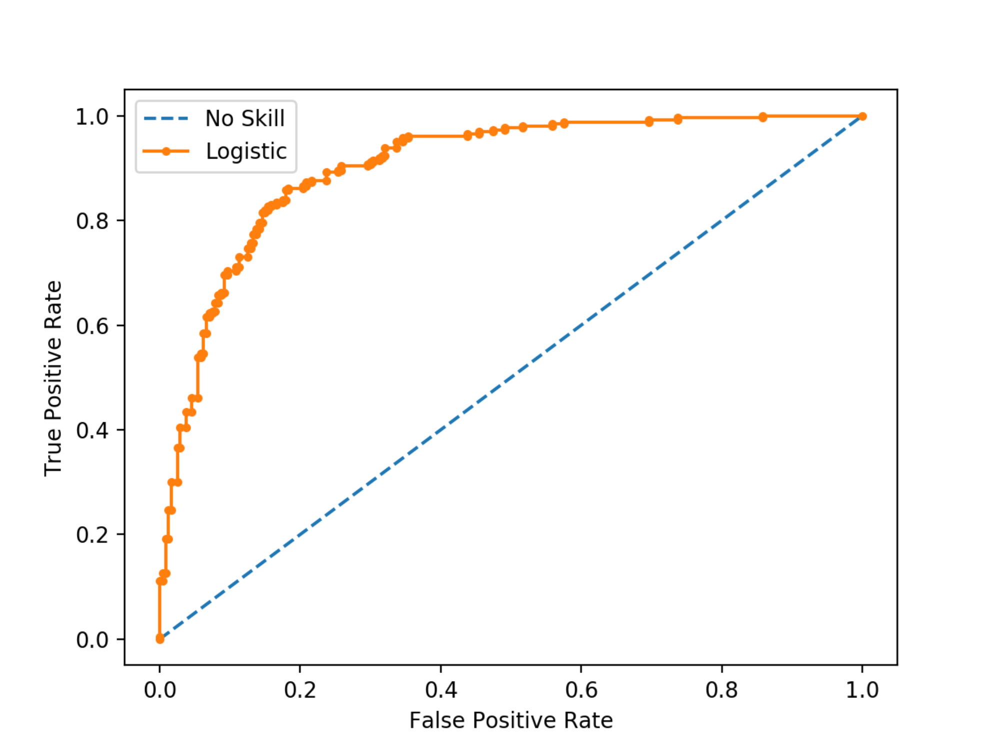
Input

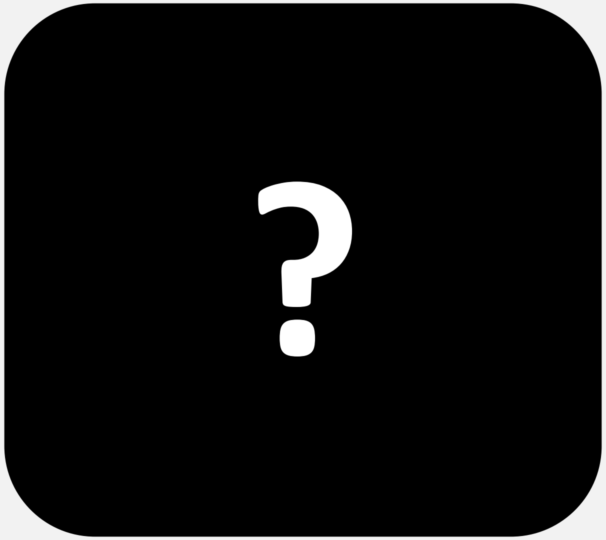
Output



Outputs

- Classification
- Metrics
  - Classification accuracy
  - Area under the curve on an ROC curve
  - Sensitivity
  - Specificity

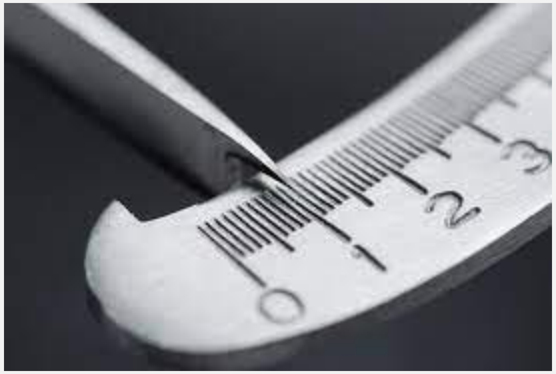




THE BLACK BOX

Types of Algorithms

Type	Strengths	Weaknesses
Logistic regression	• Minimal computational cost • Easy statistical interpretation	• Assumption of predictor independence
Bayesian networks	• Accounts for correlation among predictor variables • Can mitigate overfitting	• Computationally intensive • Weights all input variables equally
Support vector classification		
Random forest	• Typically produces high performing models with high levels of accuracy	• Computationally intensive • Can be at particular risk of overfitting
Neural networks	• Can be applied to data where relationship between variables is only vaguely understood • Works well with high dimensionality	• Processes are opaque; model is complex; can behave unpredictably



CALIBRATION

Calibration

1. Training data with actual outcomes
2. Model is fit to the training data
3. Model is tested on a new data set with actual outcomes
4. Model is released into the wild

GAMBLING AND AI

Ways AI Is Used in Gambling

- Responsible gambling
- Personalized user experience and messaging
- Engagement
- Setting odds
- Fraud detection
- Sports betting advice
- Helping players
- Chatbots for treatment
- ???

Jul 18, 2023

Sharplink Gaming to Implement Generative Artificial Intelligence to Monetize Sports Fans with the Launch of "C4 Betsense"

MINNEAPOLIS, MN / July 18, 2023 / SharpLink Gaming Ltd. (NASDAQ:SBET) ("SharpLink" or the "Company"), a pioneer of targeted conversion solutions for the U.S. sports betting and iGaming industries, today unveiled its plans for launching *C4 BetSense*, a sports industry-focused content creation and recommendation engine powered by generative Artificial Intelligence ("AI"). Utilizing advanced machine learning algorithms, generative AI is a type of technology that can produce various types of content, including text, imagery, audio and synthetic data in a matter of seconds. The *C4 BetSense* platform will leverage generative technologies to produce an endless array of tailored fan betting offers and recommendations.

"The sports industry is at an inflection point in the race to deliver fans individualized, specific betting offers that personally matter to them," stated Rob Phythian, SharpLink's Chief Executive Officer. "Imagine a sports betting game preview written in 100 different ways for 100 different fans, with relevant programmatic advertising and calls-to-action woven throughout. We believe that only scratches the surface of the potential future value of *C4 BetSense* to the sports ecosystem."

What would previously require substantial content resources and technical infrastructure will be available at a fraction of the cost through *C4 BetSense*, enabling enterprise companies – from sports media to leagues and betting operators – to efficiently engage and monetize their audiences. "We've been playing catch-up to other industries like ecommerce and streaming, where users expect a personalized menu of products and offers. Generative AI makes it possible for us to make being a sports betting enthusiast easy – from knowing your favorite teams and players to personalized bet recommendations," added Phythian.

About SharpLink Gaming Ltd.

Founded in 2019, SharpLink is a leading online technology company that connects sports fans, leagues and sports websites to relevant and timely sports betting and iGaming content. SharpLink uses proprietary, intelligent, online conversion technology to convert sports fans into sports bettors for licensed, online sportsbook operators. In addition, SharpLink specializes in helping sports media companies, leagues, teams and sportsbooks develop strategies, products and innovative solutions to drive deep fan activation and engagement with highly interactive free-to-play games and mobile applications. Further, SharpLink owns and operates a variety of real-money fantasy sports and sports simulation games and mobile apps on its platform; and is licensed or authorized to operate in every state in the United States where fantasy sports and online sports betting has been legalized. For more information, please visit the SharpLink website at **www.sharplink.com**.

Narrativa betting services

Sports Betting | eSports Betting | Online Casino

Book a Demo

Automatic Content Generation for Sports Betting

Sports Betting

AI for automated generation of long-tail sports betting content to increase organic traffic and acquisition.

Book a Demo

888 | Sportsbet.io | kindred | Bitcasino.io | codere

25 %	x25	x2
Increase in bettor retention	Content production	Customer acquisition

Narrativa NLG® transforms data and insights into relevant marketing and promotional communications and **automatically generates long-tail sports betting content** such as articles, to **increase organic traffic** and **offer additional contextual information** for bettors.**Narrativa NLP®** uses the most advanced AI language models to **generate multiple variations** of calls to action, headlines, etc., that **increase conversion**. Narrativa's technology not only creates content for the digital communities that sports betting businesses foster, but also directly assists these organizations by **boosting bettor engagement and directly impacting the bottom line in a very positive way!**

simplebet.ai

Products Solutions Resources Contact Us

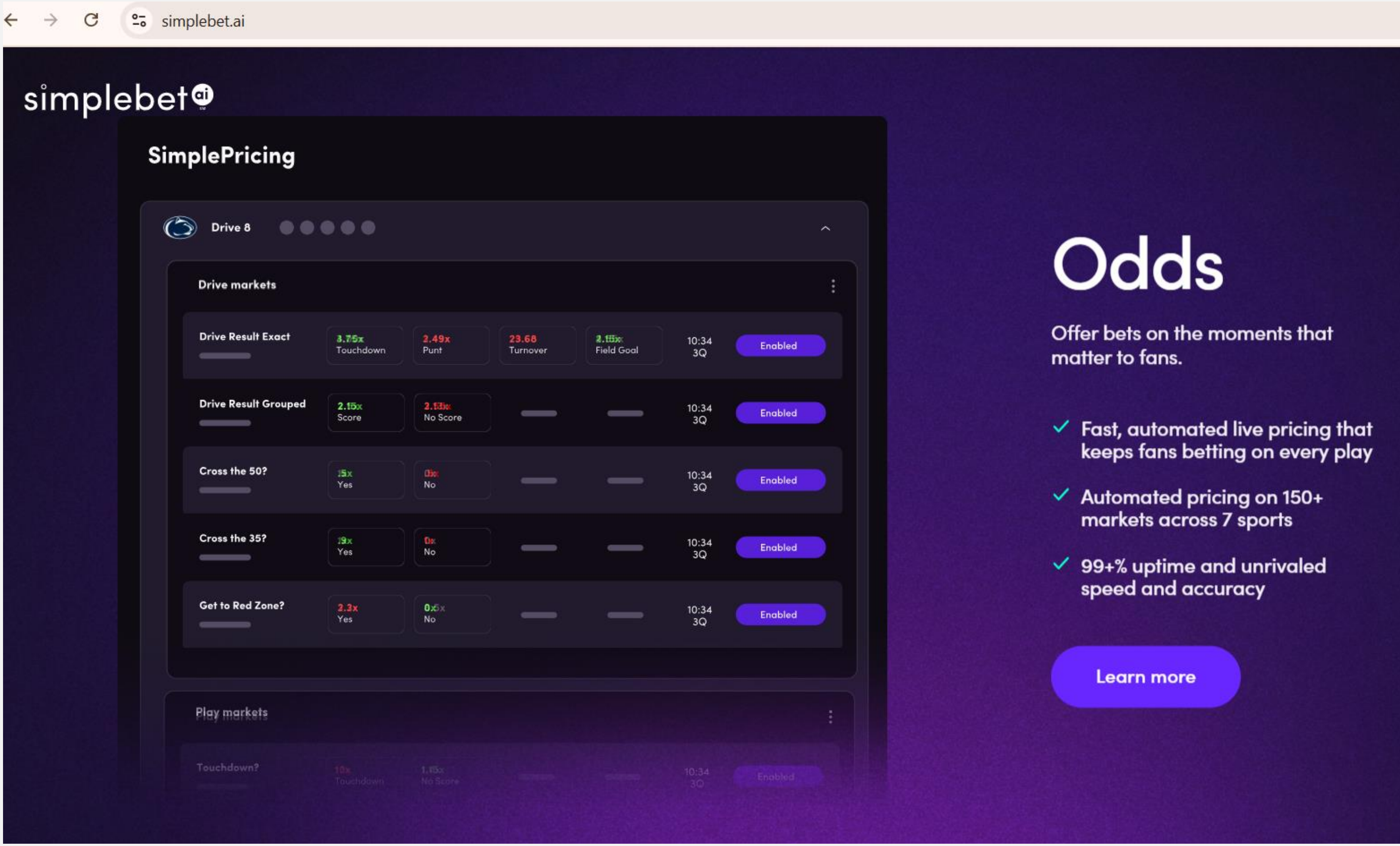
Microbetting is about instant gratification

Next pitch. Next shot. Next play. Introduce fans to the instant gratification of betting on the game's big moments. Our machine-learning models create odds, reprice, and result as action happens.

How it works +

Where it works +

Who it's for +



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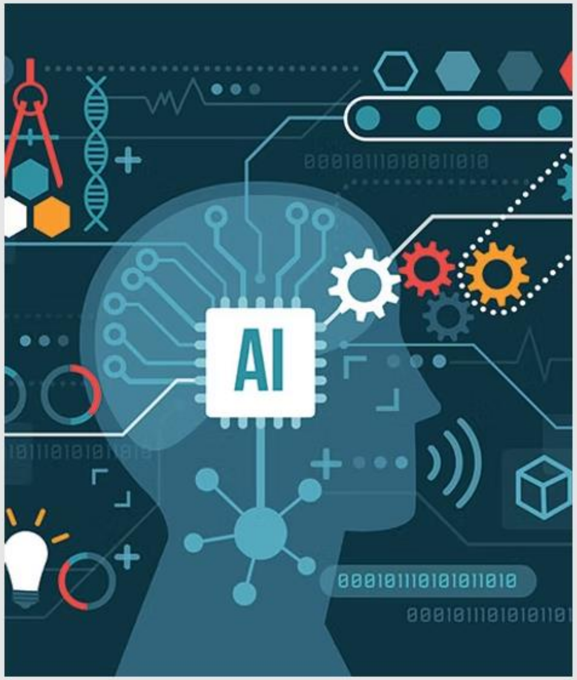
SimplePricing
Drive 8
Drive markets
Drive Result Exact
Touchdown
2.49x
Punt
23.68
Turnover
Field Goal
10:34
3Q
Enabled
Drive Result Grouped
Score
No Score
Cross the 50?
Yes
No
Cross the 35?
Get to Red Zone?
2.3x
Play markets
Odds
Offer bets on the moments that matter to fans.
Fast, automated live pricing that keeps fans betting on every play
Automated pricing on 150+ markets across 7 sports
99+% uptime and unrivaled speed and accuracy
Learn more

nqube.com

Reel AI

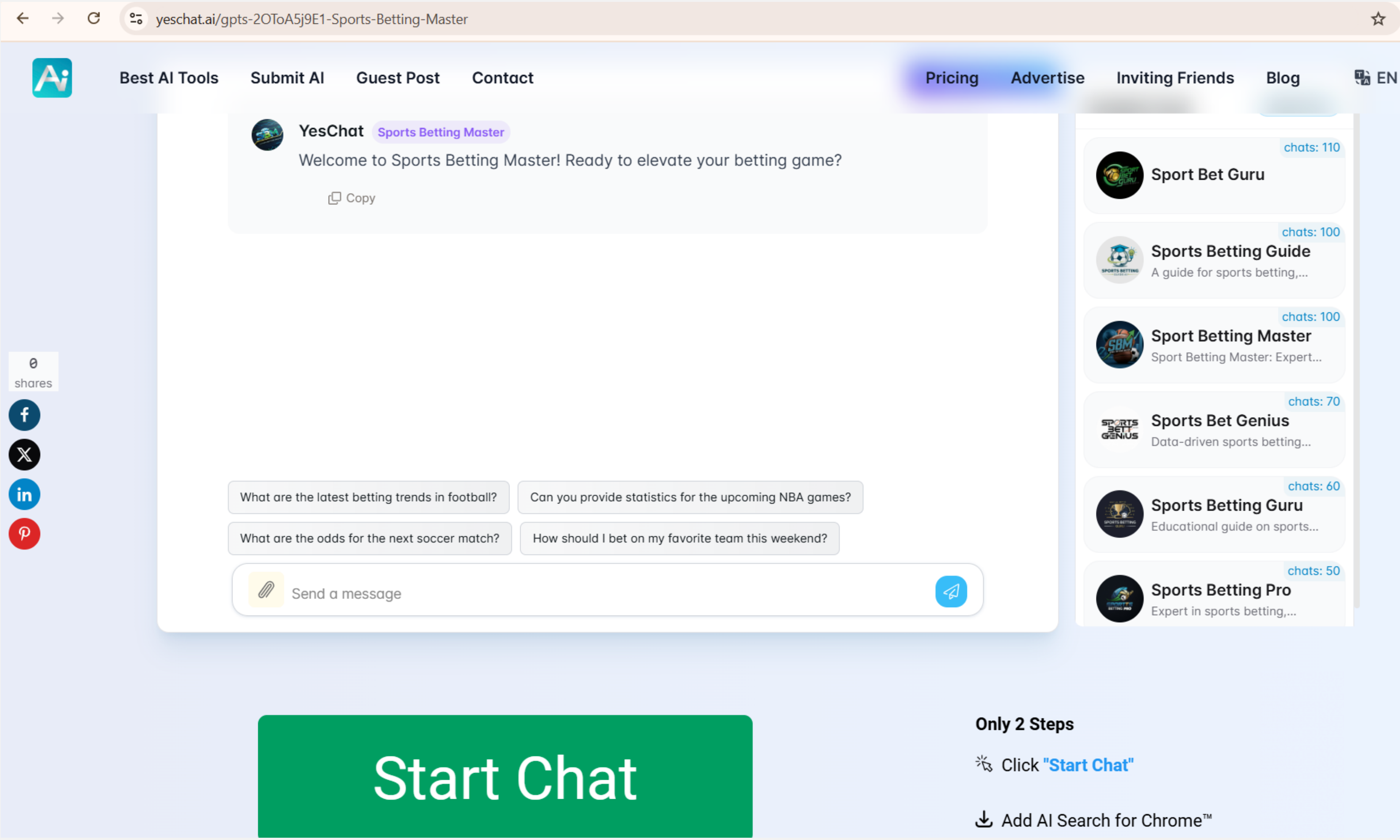
Powerful AI-driven casino technology from the inventors of non-linear slot floor optimization.



Above and Beyond

nQube's Artificial intelligence is designed to save slot floor operators time and money. It does this by searching through millions of possible slot floor configurations and exploring the total win for each one.

Our AI system has the unique ability to understand complex relationships between all of the slot machines on the floor. We use a sophisticated model of dilution and cannibalization to increase revenue for the slot floor as a whole.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Blog
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Can you provide statistics for the upcoming NBA games?
What are the odds for the next soccer match?
How should I bet on my favorite team this weekend?
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Sports Betting Pro
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Start Chat
Only 2 Steps
Click "Start Chat"
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RESPONSIBLE GAMBLING ALGORITHMS

RG Algorithm Goals

- Save time and resources and improve quality of life by intervening before clinical symptoms of disordered gambling appear.
- Need to identify the precursors (e.g., markers) to clinically manifest disordered gambling
- Use actual gambling behavior to identify, with good reliability and validity, individuals who develop gambling problems
- Utilize this/these algorithm(s) to set up an early warning system for players at risk of developing problems

Responsible Gambling Algorithms

Input

Gambling activity
Financial activity
Demographics

- Linear Models
- Decision Trees
- Bayesian Models
- Neural Nets
- Paul the Psychic Octopus

Output

Risk for gambling problems

Inputs

- Risk factors identified by past work

Anxiety

Depression

Player records

Impulsivity

Age

Early age of gambling initiation

Sensation seeking

Other risk behaviors

SES

Substance use

Gender

Inputs

Player records

Bet size

Variability

$ lost

# of bets

Gambling frequency

Deposits

$ wagered

# of gambling types

Outputs

- Risk for gambling problems
- Don’t always have access to gambling assessment outcomes
- Proxies help us group subscribers into problem gambling and non-problem gambling groups

WHIRLWIND TOUR OF RG ALGORITHMS

A Whirlwind Tour of (Academic) RG Algorithms

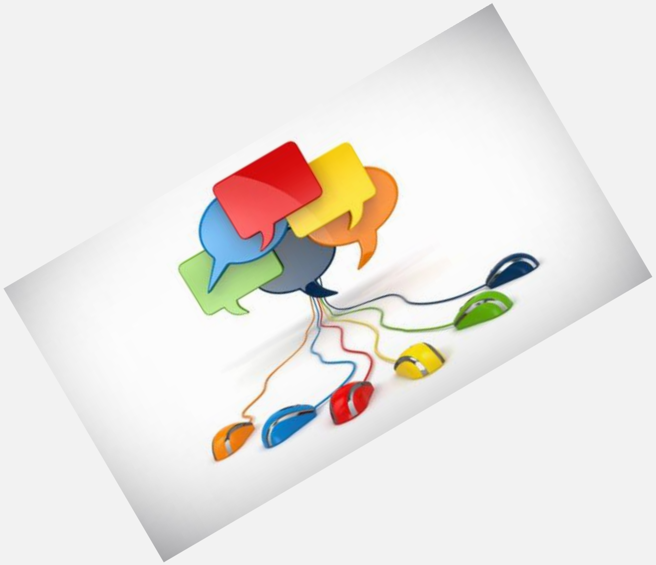
Predictors		Models	Outcomes
# of deposits $ of deposits Bet $ variability Chasing Largest single day $ wagered Most bets in one day Weekly bet $ Variation in weekly bet $ Bets per week/day Age # of gambling days Average daily loss Average loss per session Account depletion # of play breaks Multi-tabling in poker	Placing deposits shortly after placing bets Multiple deposits in a short period of time Average # of deposits per session Slope of # of deposits # of active days Slope of # of sessions #of denied deposits Volume of cash Proportion of sessions on desktop SD of session durations UK account Session duration # of wagers # of sessions $ wagered Distinct games per session Weekly bets on basketball (French)	Random forest Neural networks Logistic regression Support vector	PGSI Self Exclusion BBGS

(Perrot et al., 2022; Murch et al., 2023; Auer & Griffiths, 2023, Ukhov et al., 2021, Finkenwirth et al., 2021, Kairouz et al., 2023, Luqiens et al., 2016)

Natural Language Processing and RG
(Smith et al., 2024)

- Trained a large language model using data scraped from an online casino gambling platform discussion board to detect signs of problem gambling
- Precision was better than prior models of this type.

- A few *minor* errors:
  - Mixed up complaints with having a gambling problem
  - Missed gambling problems if not enough text surrounding phrases like “addiction” and “gambling problem”

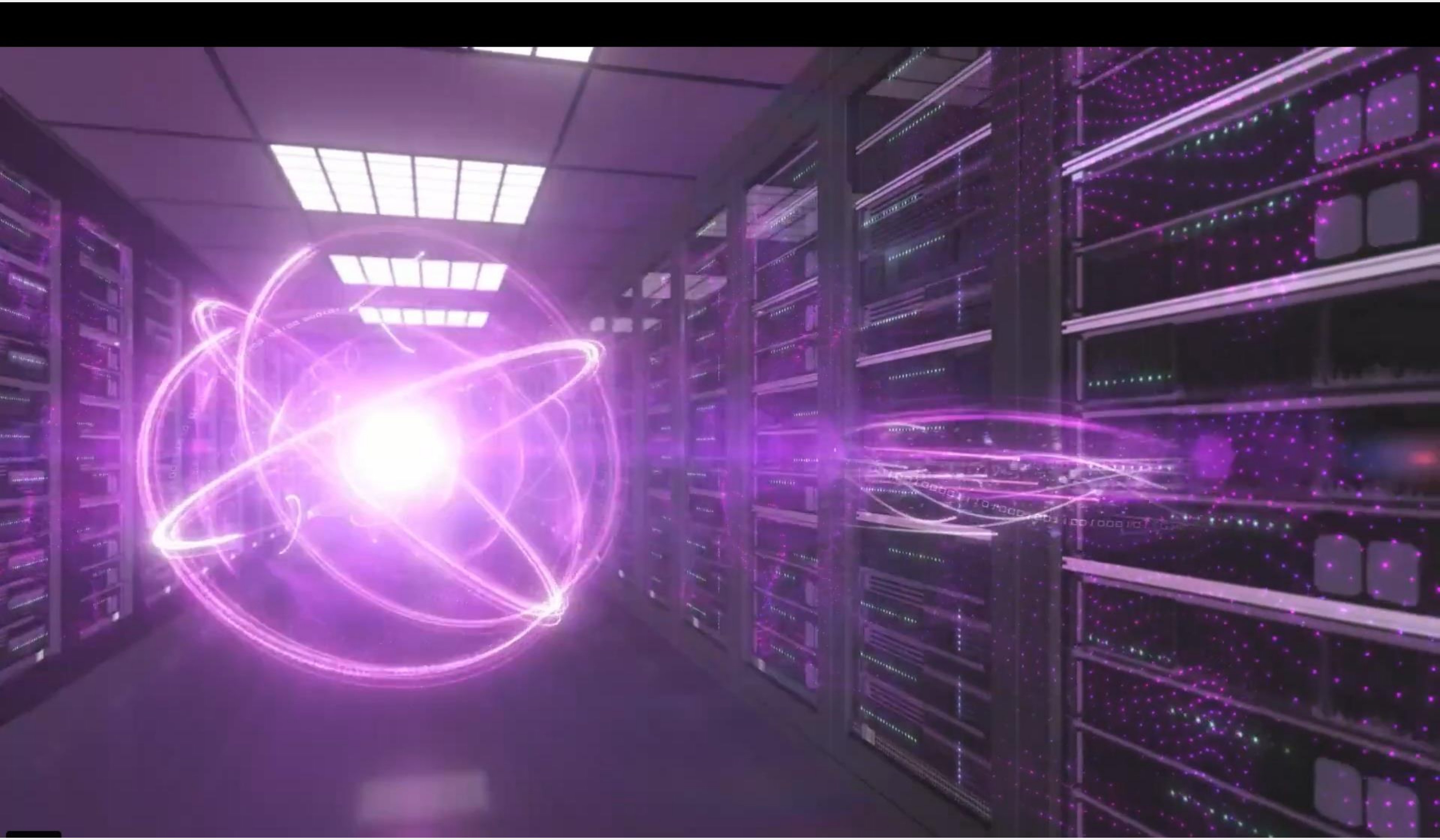


A Whirlwind Tour of (Industry) RG Algorithms

2005 2007 2009 2011 2013 2015 2017 2019 2021

- bwin partners with the Division on Addiction to use player records to identify behaviors and patterns and inform software to identify early risk factors for problems.
- Saskatchewan Gaming Corporation develops program to identify high-risk players.
- Svenska Spel offers PlayScan, where players see warning lights when their play patterns are indicative of risk.
- Kindred Group introduces its in-house Player Safety - Early Detection System (PS-EDS).
- 888 Holdings develops in-house player monitoring technology called Observer.
- bwin.party implements a DOA-designed algorithm for detecting sports bettors at risk of developing problems.
- FuSheng Interactive agrees to use PlayScan, Svenska Spel's set of tools that allow operators and players to monitor gambling.
- SkyCity Entertainment begins using Focal Research Consultants' system for identifying gamblers at risk.
- Green Gaming builds in-house algorithm to identify gamblers at risk.
- Focal Research tests their ALeRT BETTOR Protection System in the UK.
- Entain introduces the "Advanced Responsibility & Care" system for safer gambling.
- Various companies use Neccton's Mentor system to classify players as at risk based on their betting histories.
- GVC partners with Future Anthem to upgrade their existing identification algorithm to allow for earlier identification.
- Kindred Group calculates and releases the "percentage of Gross winnings revenue derived from harmful gambling."

(credit: Dr. Matthew Tom and other staff at the Division)



https://www.entaingroup.com/news-insights/insights/2021/protecting-players-with-arc/

Entain LLC ARC Player Protection System

mindway AI

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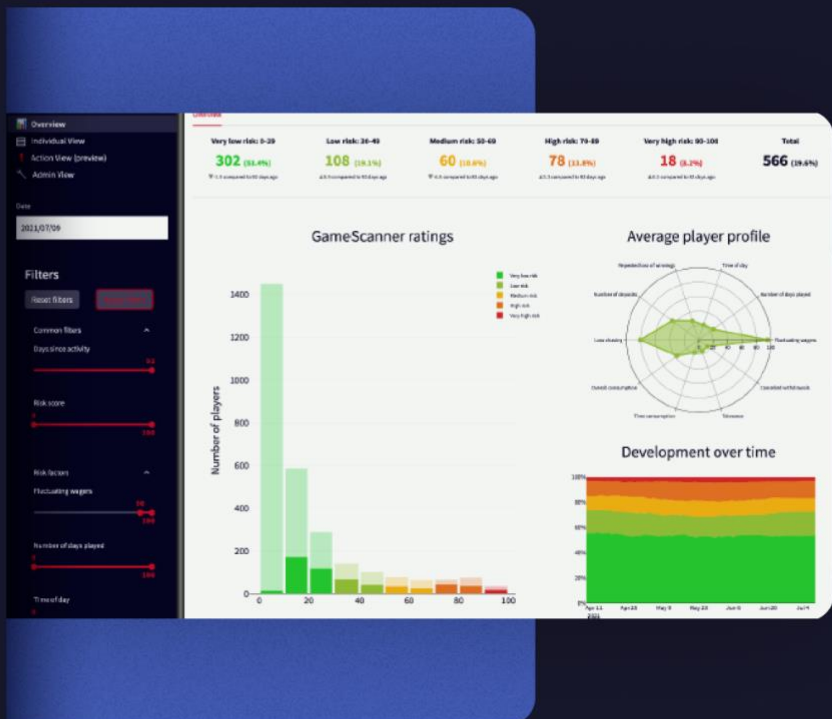
Our solutions

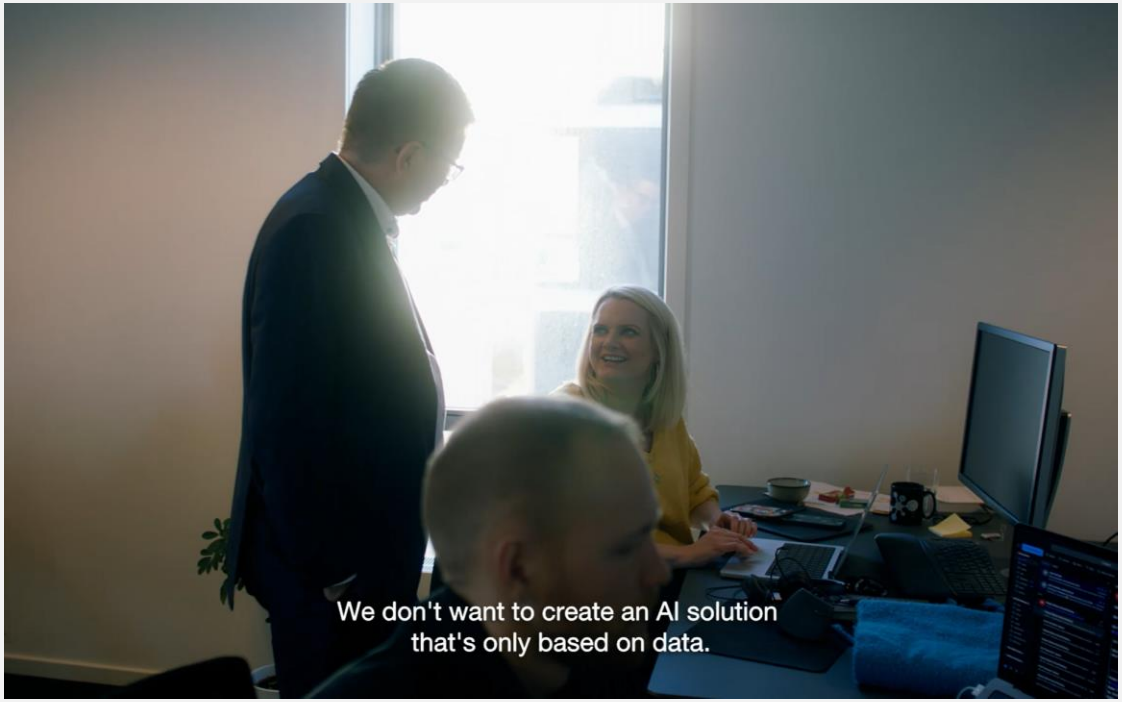


GameScanner
Early detection of at least 87% of problem cases

GameScanner is an award-winning, highly advanced safer gambling solution. Built on a combination of AI, ten years of neuroscientific research, and thorough expert assessments, it works as a virtual psychologist detecting at least 87 percent of the problem gambling cases that a human expert would detect. GameScanner allows for early detection of problem gambling behaviour, and it provides understandable and communicable information for operators to use when they reach out to players.

Read more →

https://mindway.ai/

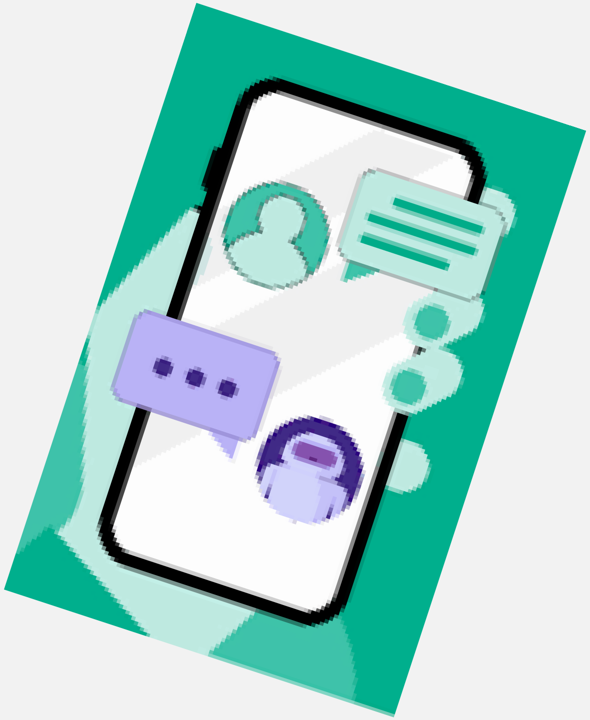


https://mindway.ai/

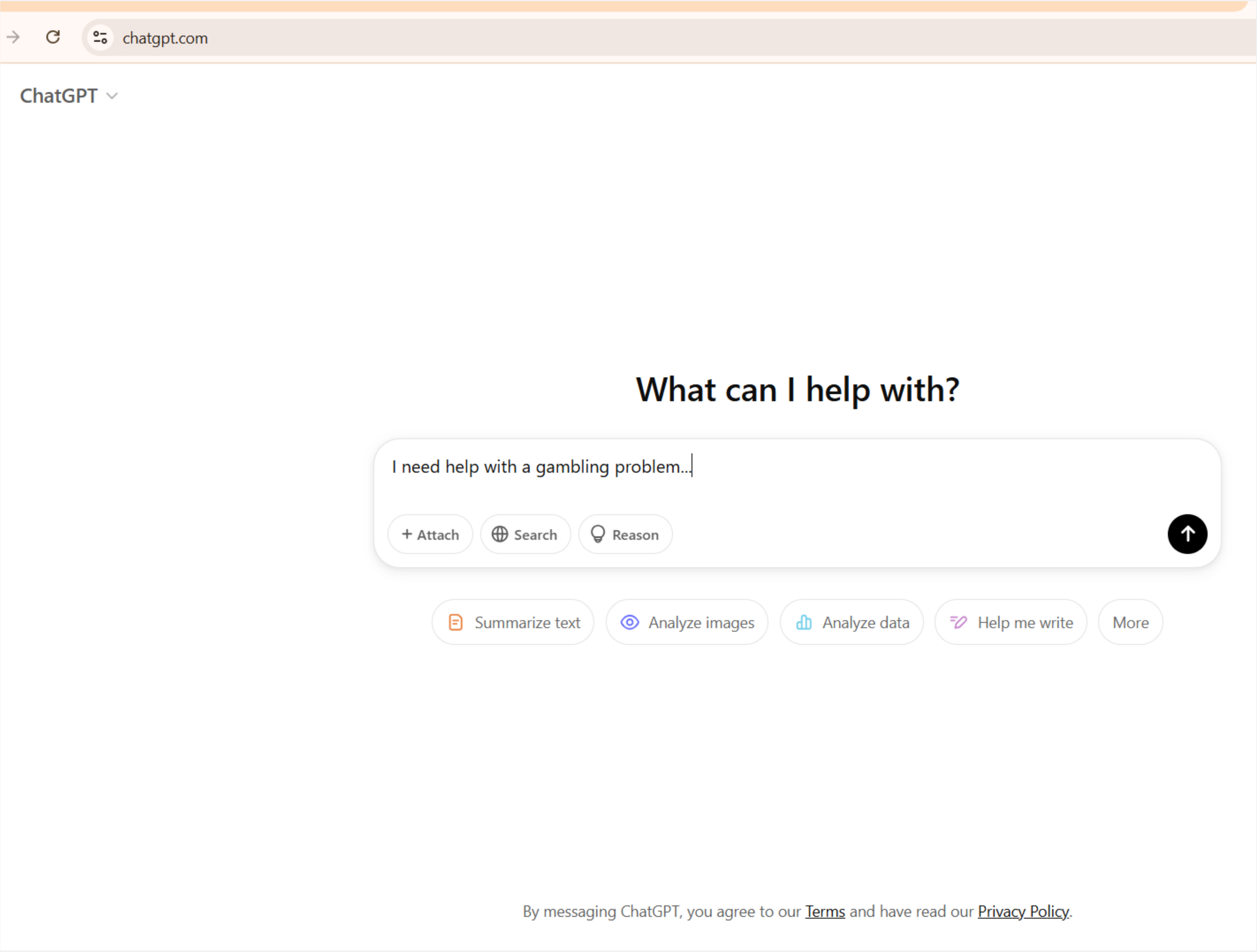
AI IN GAMBLING TREATMENT

The Role of AI in Addiction (Suva & Bhatia, 2024)

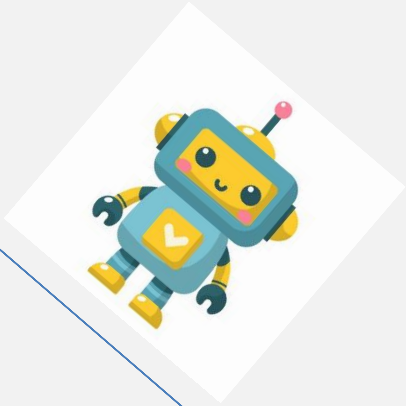
- Potential Roles
  - Identification
  - Management
  - Relapse prevention
  - Prognostication
- Problems
  - Data out only as good as data in
  - Privacy
  - Algorithmic bias



Chat GPT Example



GAMBOT (So et al., 2020)



Study Participants
(N=197)

Assessment Only (n = 101)

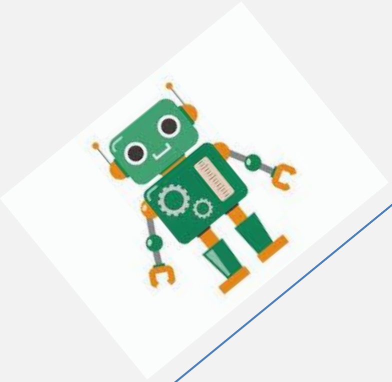
GAMBOT (n = 96)

28 weeks

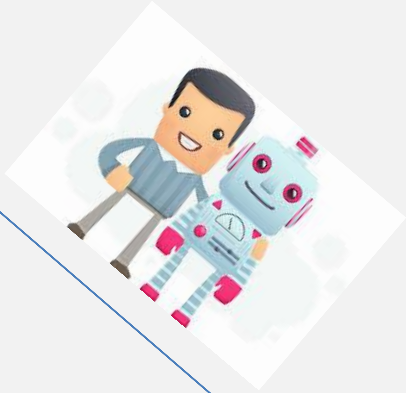
Change in PGSI: **-3.24**
(-4.35,-2.13)

Change in PGSI: **-4.38**
(-5.56,-3.20)

GAMBOT2 (So et al., 2024)



Study Participants
(N=139)



Unguided GAMBOT2
(n = 67)

Guided GAMBOT2
(n = 72)

12
weeks

Change in PGSI: **-4.3**
(SD: 6.9)

Change in PGSI: **-3.9**
(SD: 4.7)

AI PROBLEMS

Responsible Gambling Algorithms

Input

Gambling activity
Financial activity
Demographics

- Linear Models
- Decision Trees
- Bayesian Models
- Neural Nets
- Paul the Psychic Octopus

Output

Risk for gambling problems

- What are we measuring?
- Coded bias

Problems

- What are we trying to predict?
- Accuracy

- Interpretation

PROBLEMS – WHAT ARE WE MEASURING?

What Are We Measuring?

- A model is only as comprehensive as its inputs
- Meta-analysis of most common risk factors for gambling problems - (Allami et al., 2021)
  - Rated 57 potential risk factors
  - Best predictors were all gambling activity related
- MANY of the predictive algorithms based on player records generate risk levels based entirely on involvement metrics

?

PROBLEMS – CODED BIAS

Case Study: COMPAS

- COMPAS assessment was/is used within the justice system to guide supervision and case planning
- Provides a risk score that was being used to determine risk for recidivism among other things
- Was otherwise a black box

(Corbett-Davies et al., 2017; Angwin et al., 2016)

Case Study: COMPAS

- ProPublica published a report in 2016
  - Black people had higher risk scores than White people; AND
  - Black people with the same criminal background and other factors were getting much higher risk scores than White people with similar backgrounds.

Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica
May 23, 2016

ON A SPRING AFTERNOON IN 2014, Brisha Borden was running late to pick up her god-sister from school when she spotted an unlocked kid's blue Huffy bicycle and a silver Razor scooter. Borden and a friend grabbed the bike and scooter and tried to ride them down the street in the Fort Lauderdale suburb of Coral Springs.

Just as the 18-year-old girls were realizing they were too big for the tiny conveyances — which belonged to a 6-year-old boy — a woman came running after them saying, "That's my kid's stuff." Borden and her friend immediately dropped the bike and scooter and walked away.

But it was too late — a neighbor who witnessed the heist had already called the police. Borden and her friend were arrested and charged with burglary and petty theft for the items, which were valued at a total of $80.

Compare their crime with a similar one: The previous summer, 41-year-old Vernon Prater

Subscribe to the Series

https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing 1/29

(Corbett-Davies et al., 2017; Angwin et al., 2016)

Case Study: COMPAS

- Was the algorithm using race as a predictor?
  - No
- Certain factors correlate with race (e.g., zip code, poverty)
- In fact, COMPAS was equally accurate for White people and Black people – it had a classification accuracy of 61% for each group.
- BUT…

(Angwin et al., 2016; Christian, 2020)

Case Study: COMPAS

- …when it was wrong, how it was wrong differed
  - Black people were 2x more likely to be rated higher risk but NOT re-offend, whereas White people were 2x more likely to be rated low risk but go on to re-offend

(Angwin et al., 2016; Christian, 2020)

Training Data Matters

- An algorithm is at the mercy of its training data
- Training data specifies "correct" outputs – algorithm learns from the training data and then applies its model to new data
    - Might not be fully representative (e.g., Faces in the Wild dataset)
    - Might have biases "baked in" (e.g., recidivism algorithms)
    - Can replicate or amplify human biases (e.g., Microsoft's chatbot)

(Lee et al., 2024; Friis & Riley, 2023; Okidegbe, 2007; Christian, 2020)

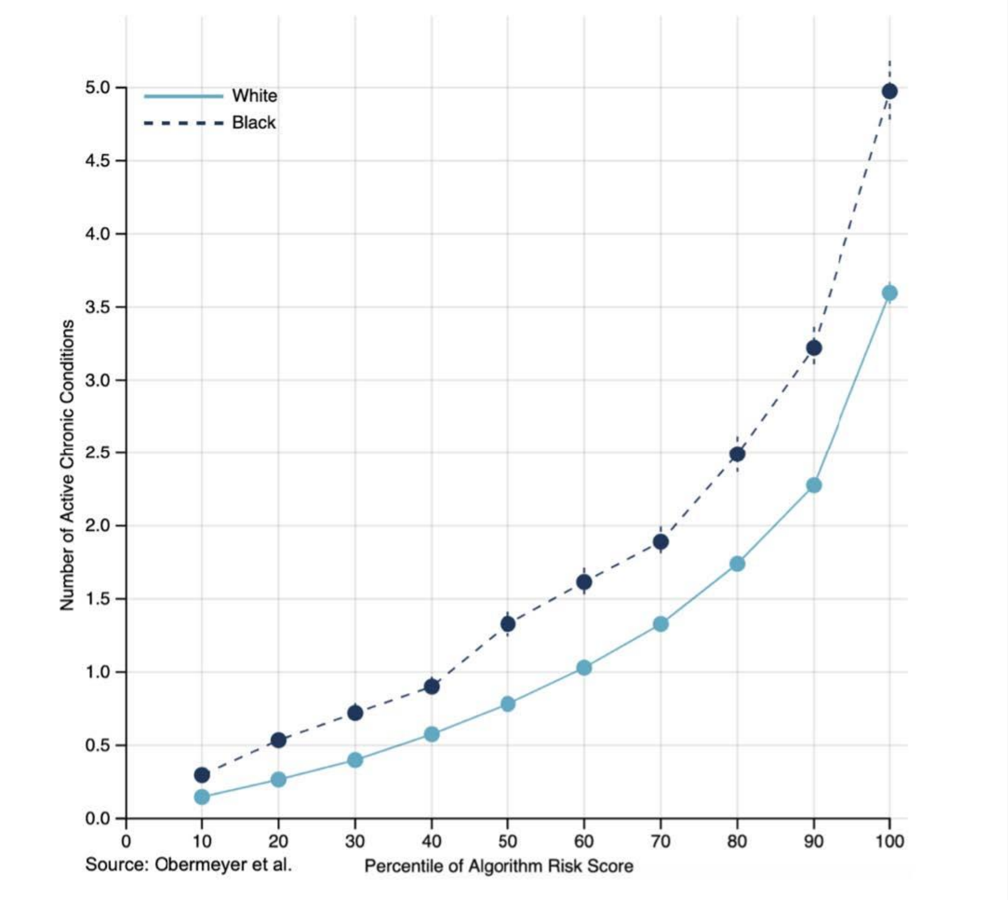
Coded Bias Applied to Gambling

- Gambling risk algorithms could very well have coded bias
- Example: Affordability indices
  - Zip code, geographical markers, poverty
  - Career, salary, etc.
- No current efforts to detect potential bias

PROBLEMS – WHAT ARE WE TRYING TO PREDICT?

Example

- Ideal target: patients who are likely to get sick
- Actual target: patients who seek treatment and generate health care costs



(Bembeneck et al., 2021)

Applied to Gambling

- Examine our proxies
  - Are they really equivalent to gambling problems?
  - How do they differ?
- Context
  - Who was the sample used to develop the algorithm?
  - Are they equivalent to the individuals for whom the algorithm is deployed?

PROBLEMS – ACCURACY

RG Algorithm Accuracy

- Most RG predictive algorithms that have been tested aren’t particularly accurate
  - This is not unique to gambling – problem with most low base rate occurrences
- Problem with overfitting (Ghaharian et al., 2023; Philander, 2014)
- Might be accurate at one level but not another
  - Differentiate high risk from others, but unable to differentiate moderate risk from low risk (Murch et al., 2023)

What does it mean to be accurate?

	Actual GD	Actual not-GD
Predicted GD	0	0
Predicted not-GD	10	490

Classification accuracy: 490/500 = 98%
Sensitivity: 0/10 = 0%
Specificity = 490/490 = 100%

- 98% accurate could be really inaccurate if the base rate is low
- Need to look carefully at sensitivity and specificity

PROBLEMS - INTERPRETATION

Interpretability

- Most accurate models tend to be the most opaque (and vice versa), and that can be dangerous
- If not fully understood, algorithms can create feedback loops

(Ghaharian et al., 2023; Christian, 2020)

Context

- Make sure an algorithm is being used for the purpose it is supposed to be used for and that its context is understood
  - e.g., finding that betting on basketball is a particularly salient risk factor (Kairouz et al. 2023)…
    - …in France

SOLUTIONS

Problems		Solutions
What are we measuring?	→	Move beyond involvement
Coded bias	→	Testing
What are we predicting?	→	Merge records & self-report
Accuracy	→	Tiered systems
Interpretation	→	Treat as probabilistic

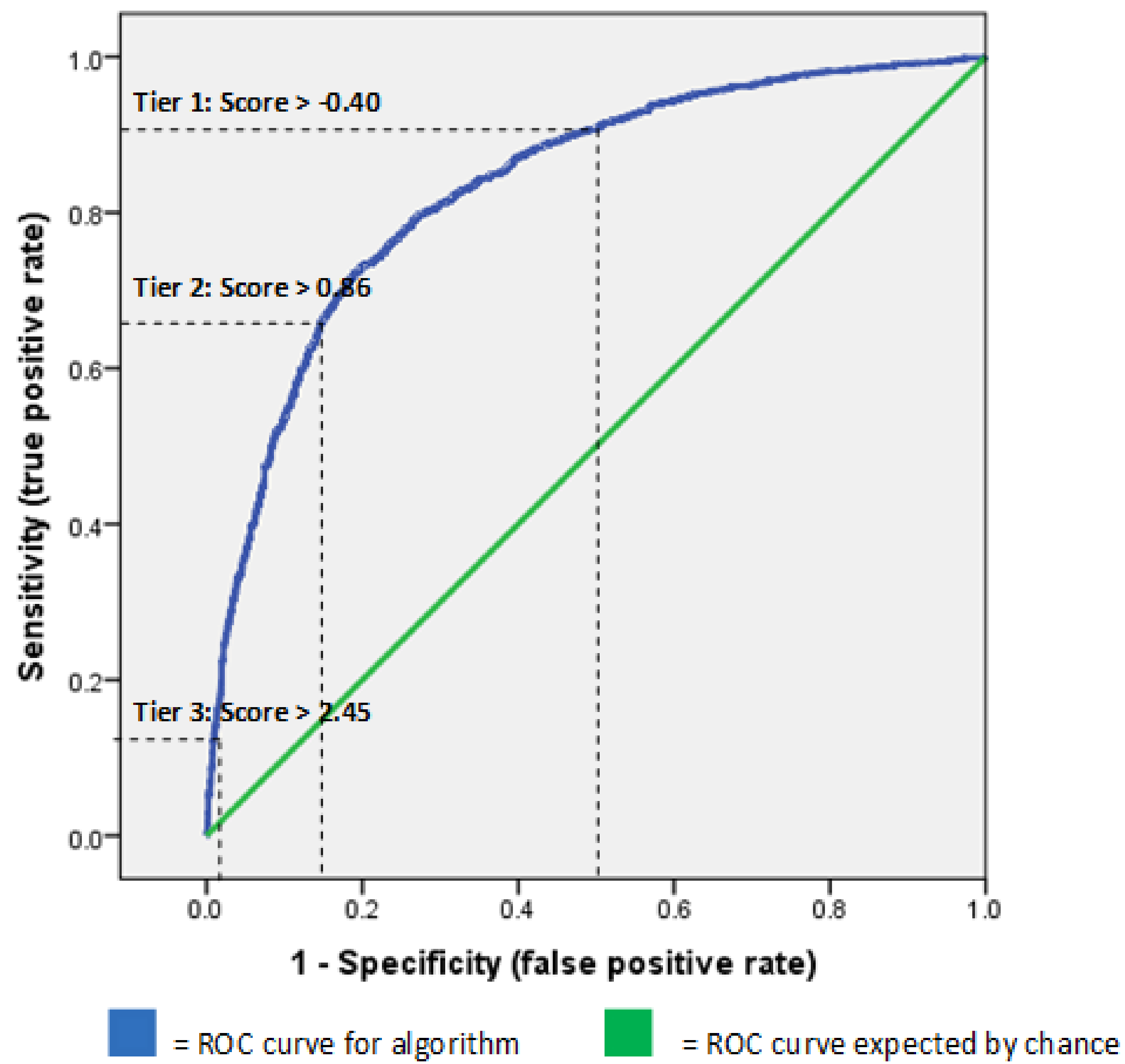
Messaging & Feedback

- No current method for avoiding discrimination against protected attributes in machine learning
- Doesn’t work to just ignore the actual attributes since other features are correlated with them.
- Doesn’t work to just ensure that the decision is independent of the protected attribute
- Can require equalized odds within groups but might change meaning of risk scores
- Hardt et al., 2016 proposed a test to test for the level of discrimination in an algorithm

(Hardt et al., 2016; Bembeneck et al., 2021)

Problems	Solutions
What are we measuring?	Move beyond involvement
Coded bias	Testing
What are we predicting?	Merge records & self-report
Accuracy	Tiered systems
Interpretation	Treat as probabilistic

Messaging & Feedback



Tier 1: Score > -0.40
Tier 2: Score > 0.86
Tier 3: Score > 2.45
1.0
0.8
0.6
0.4
0.2
0.0
Sensitivity (true positive rate)
0.0
0.2
0.4
0.6
0.8
1.0
1 - Specificity (false positive rate)
= ROC curve for algorithm
= ROC curve expected by chance

Problems	Solutions
What are we measuring?	Move beyond involvement
Coded bias	Testing
What are we predicting?	Merge records & self-report
Accuracy	Tiered systems
Interpretation	Treat as probabilistic

Messaging & Feedback

- Choose models that allow us to see under the hood (Christian, 2020)

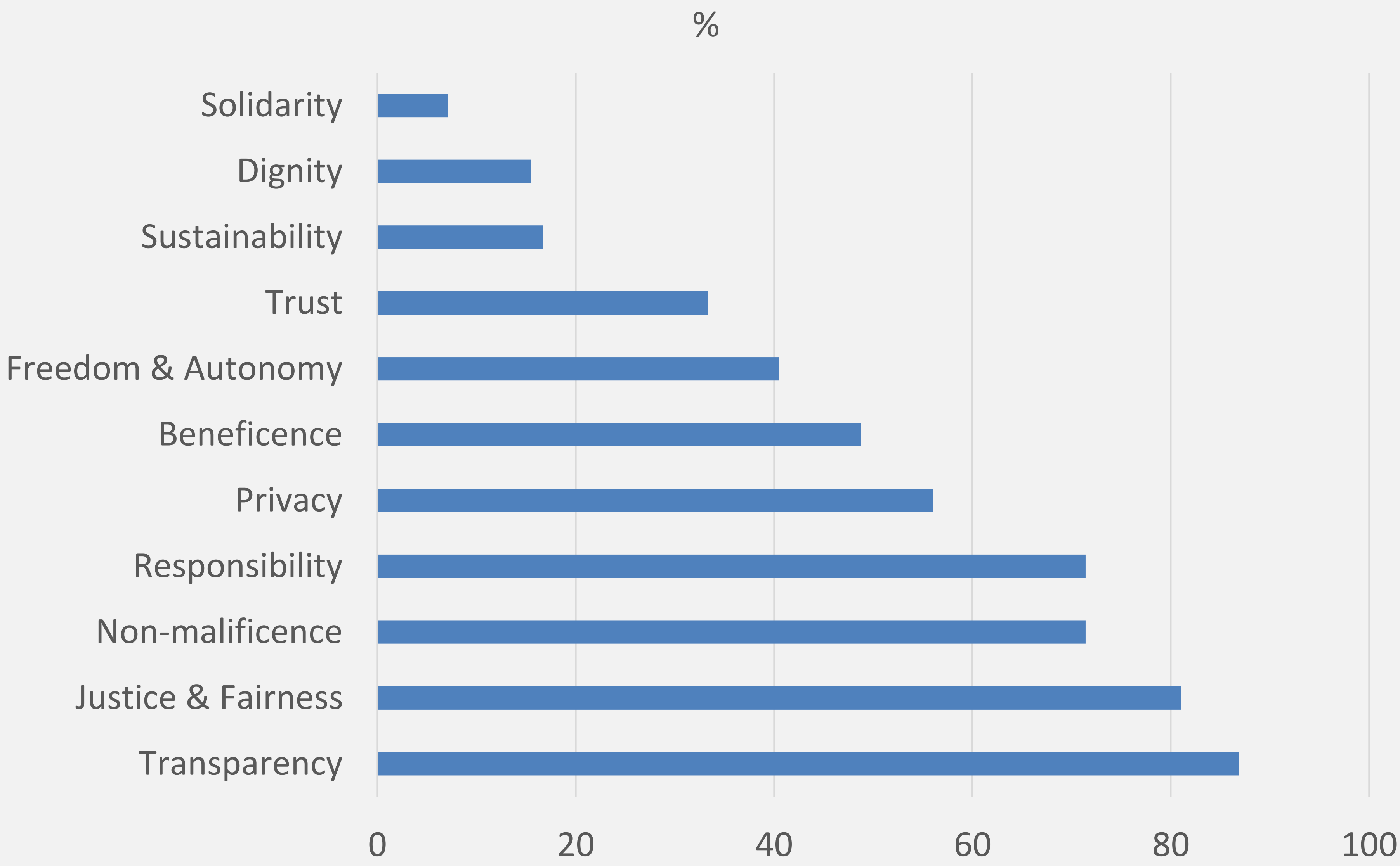
- Consider the population and context
  - Some models being developed separately for different game types (e.g., Ukhov et al., 2021)

MESSAGING AND FEEDBACK

- MUST evaluate our messaging and interventions based off of algorithms, as well
- Might need to be tailored to different populations
- Might have different effects than we expect

Principles & Guidelines for Ethical AI

(Jobin et al., 2019)



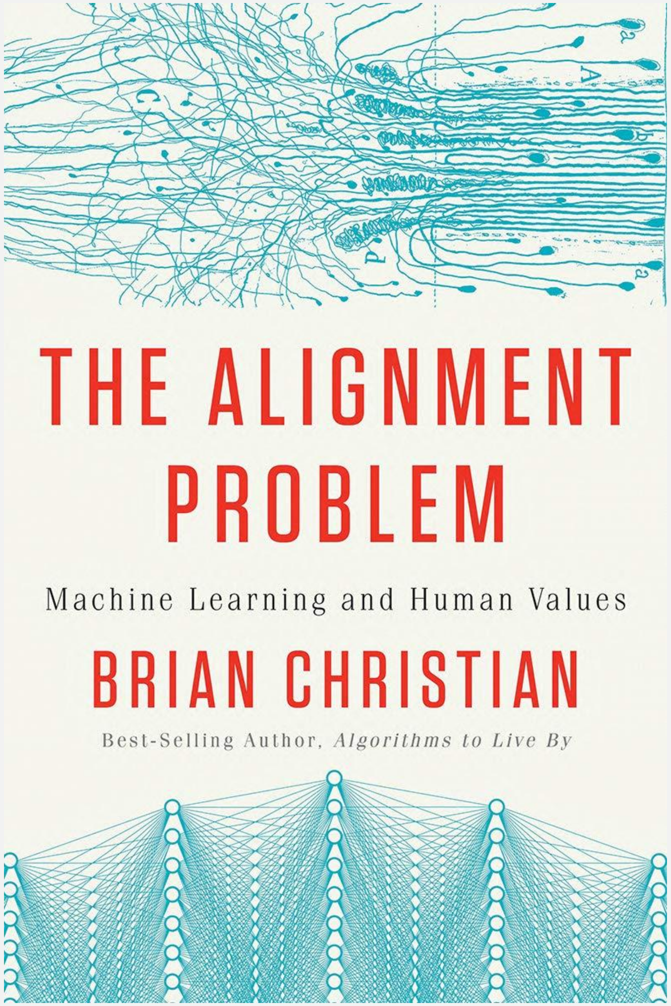
TAKE-HOME POINTS

1. When people are referencing Artificial Intelligence, make sure they explain what they mean. Could be nothing more than a logistic regression model (or not even that).
2. Training data matters. We're most tuned into this for coded bias, but it matters for interpretation, for claims of accuracy, for everything.
3. No matter how good the training data and the accuracy, algorithms are probabilistic models.

1. AI has potential for prevention and intervention.
2. For every AI model built to help prevent and detect gambling problems, there is one to help engage gamblers and increase revenue.
3. Prevention of gambling harms can benefit from raising awareness of AI among gamblers (e.g., powerful AI models being used to set the odds for sports gambling).

References

- Best book for a deep dive:



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Additional Resources

- Questions? snelson@hms.harvard.edu
- www.divisiononaddiction.org
  - Division on Addiction's main website
  - Current projects and publications
- www.basisonline.org
  - Brief science reviews and editorials on current issues in the field of addictions
  - Addiction resources available, including self-help tools
- https://www.facebook.com/divisiononaddiction
  - The Division's facebook page