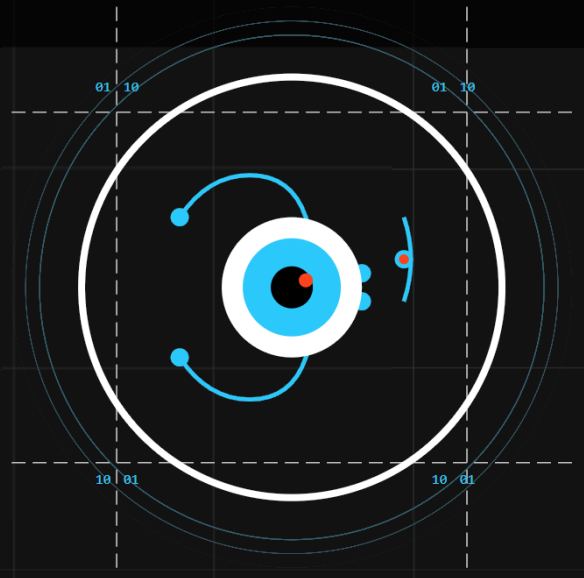
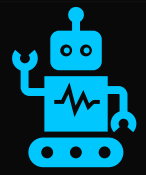
AI AND MACHINE LEARNING

Understanding Intelligence in the Digital Age

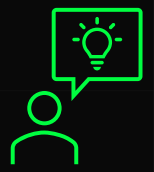


PROFESSOR RYAN HAAS

WHAT IS ARTIFICIAL INTELLIGENCE?



Artificial Intelligence (AI) is the ability of a computer or a machine to mimic human intelligence.



AI systems can perform tasks such as recognizing speech, making decisions, and solving problems.

Examples: Virtual assistants (like Siri), facial recognition, and self-driving cars.

TWO PRIMARY CATEGORIES OF AI

Analytic AI

AI systems designed to identify patterns, trends, and apply rules or access knowledge systems without dynamic generative ability.

Core function: Analysis, classification, prediction based on existing data.

- Recommendation systems (Netflix, Spotify)
- Fraud detection algorithms
- Medical diagnostic tools
- Traditional search engines

Generative AI

AI systems designed for creation and content generation.

Core function: Producing new content, text, images, code, etc.

- ChatGPT, Claude (text, code generation)
- DALL-E, Midjourney (image generation)
- GitHub Copilot (code generation)

APPLICATIONS ACROSS DOMAINS

HEALTHCARE

Analytic: Diagnostic AI for pattern recognition in medical imaging

Generative: Medical report generation and treatment plan creation.

BUSINESS

Analytic: Market analysis and trend prediction

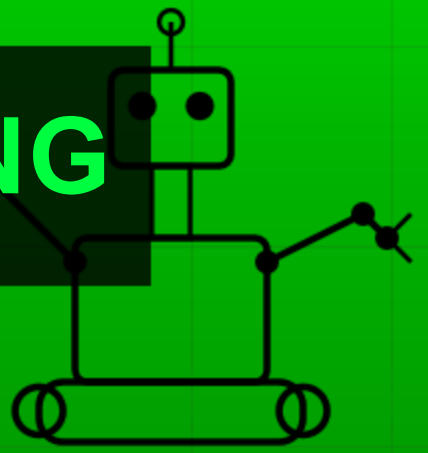
Generative: Marketing copy generation and product descriptions

EDUCATION

Analytic: Learning analytics and performance tracking

Generative: Personalized content creation and adaptive learning materials

ANALYTIC: MACHINE LEARNING



THE THREE-STEP PROCESS

WHAT IS MACHINE LEARNING?

Machine Learning (ML), a major subset of Analytic AI, allows computers to learn from data and improve over time without being explicitly programmed.

Category	**Analytic AI**
Focus	Pattern recognition and prediction from data
Example	Imagine teaching a dog to sit by giving it treats when it sits correctly. Over time, the dog learns to sit on command.

AI > ANALYTIC > MACHINE LEARNING

THE THREE-STEP ML PROCESS

The 3-Step Machine Learning Process

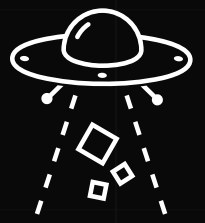
View Document ↗

1 Data Collection

Gathering relevant, representative datasets

Quality considerations:

- completeness
- accuracy
- relevance



2 Training

Algorithm learns patterns from training data through iterative improvement.

Study analogy:
studying for a test using practice problems.

3 Prediction

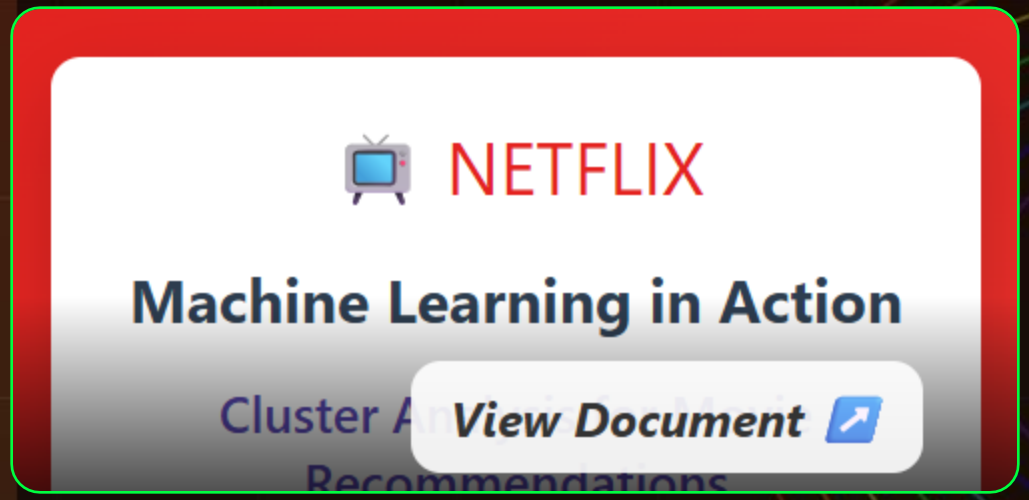
Making predictions on new, unseen data with performance evaluation.

Study analogy:
Applying what you learned to solve new problems.

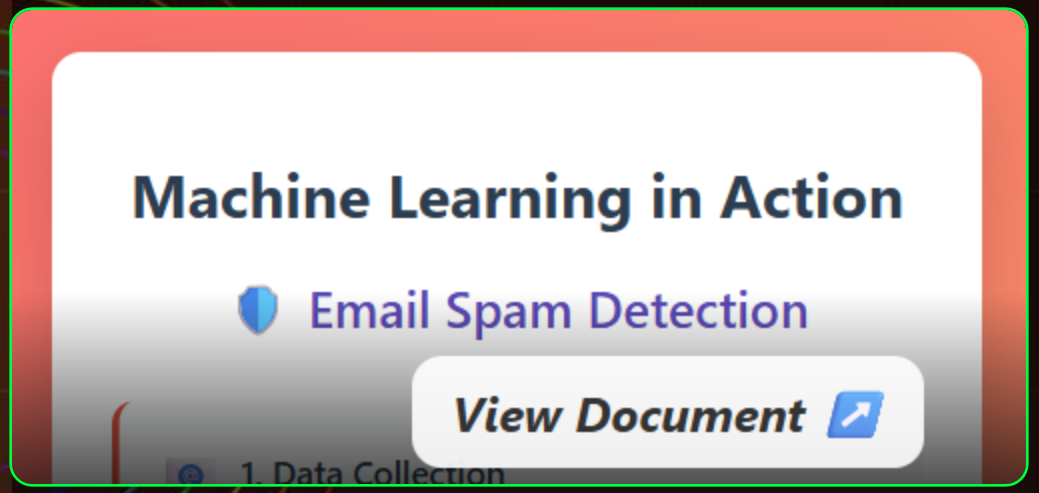
AI > ANALYTIC > MACHINE LEARNING

ML IN ACTION: REAL EXAMPLES

Netflix Recommendations



Email Spam Detection



AI > ANALYTIC > MACHINE LEARNING

COMMON ML PITFALLS

⚠ Overfitting

Cram studying: Memorizing specific practice problems instead of understanding concepts.

In machine learning: Too much "cram studying" on specific training data. Model performs well on training data, but fails on new, slightly novel data.

Real-world Impact: Poor generalization to novel situations. E.g., training set featured people crossing street on crosswalk. Camera vision doesn't recognize person crossing street without a crosswalk present.

⚠ Bias in Training Data

Would you trust a history book that cites only one historian for all its information?

Would you write a literature review based only on the publications of one team of researchers?

Models inherit and amplify the biases present in training data.

Real-world Impact: Discriminatory outcomes in hiring, lending, criminal justice.

AI > ANALYTIC > MACHINE LEARNING

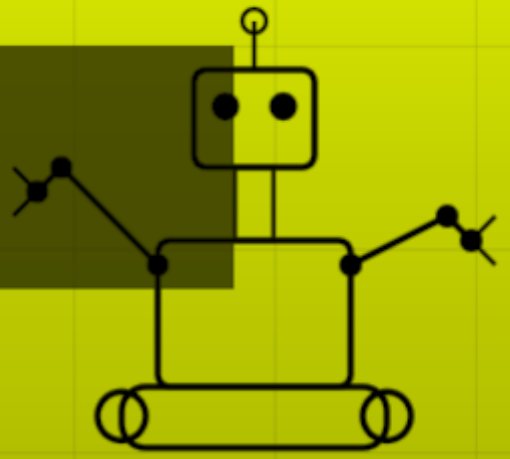
IMPACTS OF ML BIAS

IMPACTS OF ML BIAS

"Dirty Data, Bad Predictions" (Shultz & Crawford, 2019):

- Analysis of 13 jurisdictions where predictive policing systems deployed during periods when the police dept's were under investigation for unconstitutional practices:
  - Chicago: Strategic Subject List (SSL) used arrest records from a period of racial bias.
  - New Orleans: Palantir system likely used data from a period of pervasive civil rights violations.
  - Maricopa County: Numerous municipalities share data with a department that engaged in systematic racial profiling.
- **Feedback Loops**: When predictive systems are trained on biased data, they direct more policing to already over-policed areas, creating a positive feedback loop of negative consequences (enforcement patterns not reflective of actual crime rates)
- **Recommendations**: More rigorous oversight, accountability, & transparency. Historical data from periods of documented misconduct should be restricted from use in predictive systems.

NEURAL NETWORKS



FROM SIMPLE CONCEPTS TO COMPLEX APPLICATIONS

NEURAL NETWORKS: Foundation for Modern AI

- Inspired by biological neural networks
- Interconnected nodes (neurons) processing information
- Pattern recognition through layered processing

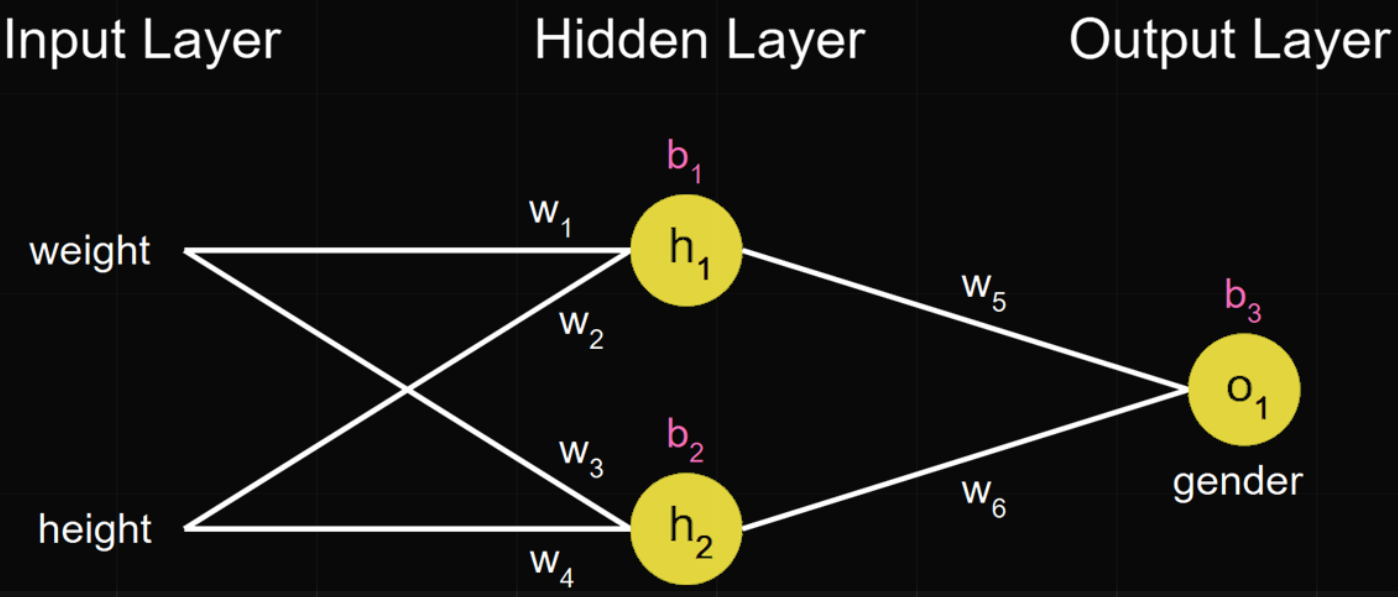
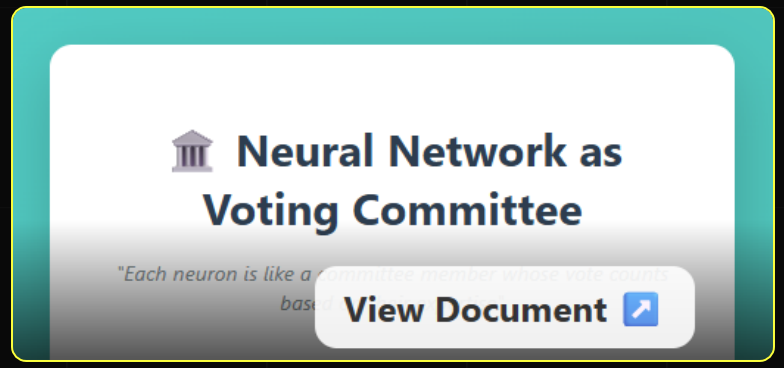


Image adapted from "Machine Learning for Beginners: An Introduction to Neural Networks" (2022) by Victor Zhou.

NEURAL NETWORKS: The Committee Analogy

Neural nets are analogous to committees that vote.

Their weights determine how much their votes count in the final decision.



Input layer: Junior members with equal votes analyzing key features (edges, corners, lines, curves)

Hidden layer 1: Specialists focusing on specific aspects (shape, texture, size)

Hidden layer 2: Senior analysts with broader insights for complex pattern recognition

Output layer: Decision makers announcing final weighted decision (Dog 85%, Cat 12%, Bird 3%)

WE USE ML TO TRAIN NEURAL NETWORKS

Neural networks are trained using machine learning. Example:

Goal: create neural network that can receive a picture of dog or a cat as input and output which animal the picture contains.

i **Define The Network Structure**

Input Layer → Hidden Layers → Output Layer

(image pixels) (feature learning) ("dog" or "cat")

ii **The Three-Step ML Process**

1 Data Collection

2 Training

3 Prediction

WE USE ML TO TRAIN NEURAL NETWORKS

Neural networks are trained using machine learning. Example:

Goal: create neural network that can receive a picture of dog or a cat as input and output which animal the picture contains.

1. Data Collection

Gathering thousands of labeled images

Cat images: Labeled as **0**

Dog images: Labeled as **1**

2. Training

Forward Pass (Guessing)

1. Feed an image (say, dog) into the net.
2. The net multiplies input values by weights & applies activation functions (math that lets it learn complex patterns).
3. Output layer gives probabilities:
   - Cat: 0.15
   - Dog: 0.85 → Guesses dog

Comparing the Guess

We know the **true label** is dog. The network guessed 0.85 for "dog", so it did okay, but not perfect.

3. We use a *loss function* to measure how far off the prediction is, e.g.:

Loss = (Predicted - True)²

Lower loss = better prediction.

4. Adjust the weights: the committee members that voted correctly get slightly more voting power.

Repeat the guess/comparison many times (studying to improve knowledge).

3. Prediction

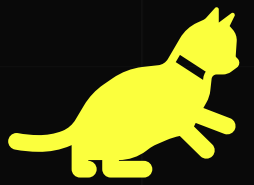
After training:

Now show the network a new dog that wasn't in the training. It can say:

"I'm 92% sure this is a dog".

LET'S TRAIN A NEURAL NET!

Training a Pet Recognition System!
Using Google's Teachable Machine, we'll create a basic pet classifier.



1. Create basic pet classes (dogs, cats) and populate with images
2. Test with sparse training using students' shared pet images
3. Add more training data on specific dogs and cats from pre-existing labeled sets
4. Observe improved predictions on students' images
5. Demonstrate bias: unknown objects predicted as the class with more training data

Learning Objective
Experience firsthand how training data quality and quantity affects model performance.

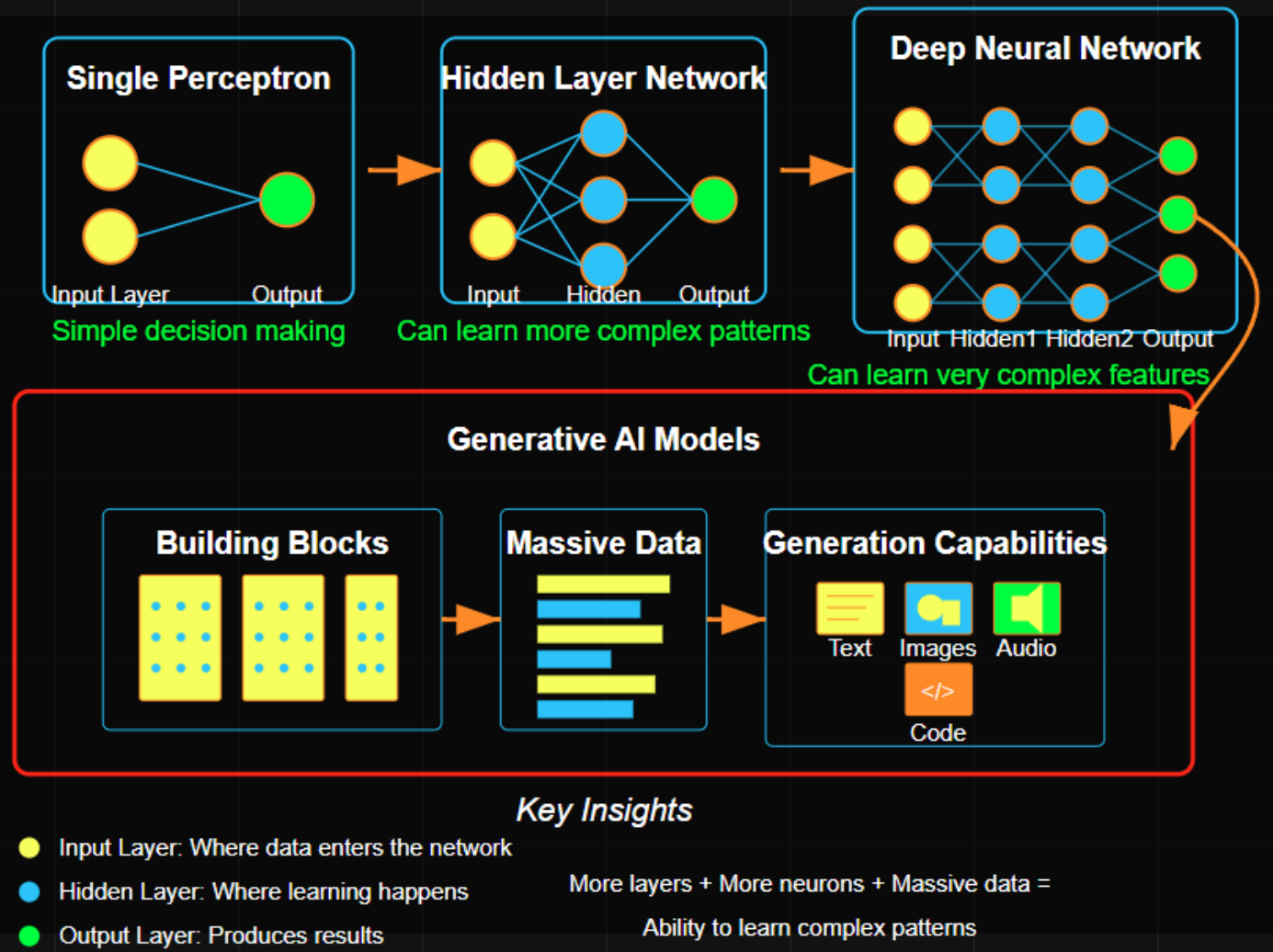
LARGE LANGUAGE MODELS AND GPTs

UNDERSTANDING AND EFFECTIVELY USING GENERATIVE AI

NEURAL NETS: FROM SIMPLE TO COMPLEX

Generative AI models are very large neural networks which make them capable of learning very complex features!

There are several types of Generative AI models, some are specialized for image/video generation. We will take a closer look at the most prolific type: the **Large Language Model**.



AI > GENERATIVE

WHAT IS A LARGE LANGUAGE MODEL [1]

A large language model (LLM) is a type of deep learning model "trained on immense amounts of data, making it capable of understanding and generating **natural language** and other types of content to perform a wide range of tasks".

A GPT (generative pre-trained transformer) is just a popular type of LLM used in generative AI chatbots.

How LLMs Learn:

ocessing: Billions of text examples *tokenized* into machine-readable units

Machine Learning: Model learns patterns without labeled data

Transformer Architecture:

- ***Self-attention*** mechanism tracks relationships b/t words
- Tokens mapped to embeddings (vector representations)
- Query, key, and value vectors enable **contextual understanding**

Parameter Optimization:
Model weights adjusted in training process

Fine-Tuning: Additional training on specific datasets for specialized applications

1. *What are large language models (LLMs)?*. 2025. Cole Stryker, *IBM Think*.

AI > GENERATIVE > LARGE LANGUAGE MODELS

THE PREDICTION REALITY

⚠ LLM = next word predictor

When LLMs provide information, they are primarily making predictions based on training data, not accessing real-time databases.

Implications:

- Accuracy varies and requires verification.
- Sources may be hallucinated or misattributed.
- Fact-checking remains essential
- Models can sound confident while being incorrect

☑ Benefits of LLMs

Communicate in chat-style interface using natural language, rather than specific code or syntax.

Democratizes access to AI capabilities:

- Brainstorm and prototype creative solutions
- Edit and revise text
- Summarize information, spot trends
- Visualize topics, information
- Act as a tutor for information provided

CLEAR PROMPTING

A structured approach to communicating with AI

C

Clarity

Specific, well-defined goals

L

Logistics

Practical details, input types, steps, desired output

E

Examples

Demonstrate intended output, specify what you DON'T want

A

Audience

Target population characteristics and needs

R

Refinement

Iterative improvement through feedback

AI > GENERATIVE > LARGE LANGUAGE MODELS

INFORMATION LITERACY IN THE AI ERA

Retrieval-Augmented Generation (RAG)

- LLMs accessing and synthesizing information from databases, incl. web search results
- Integration with search engines (Google's Gemini Overviews, Bing Chat)

Traditional Search

- Returns a list of links to relevant pages
- User evaluates and synthesizes information

AI-Enhanced Search

- Provides synthesized answers from multiple sources
- AI pre-processes and summarizes information

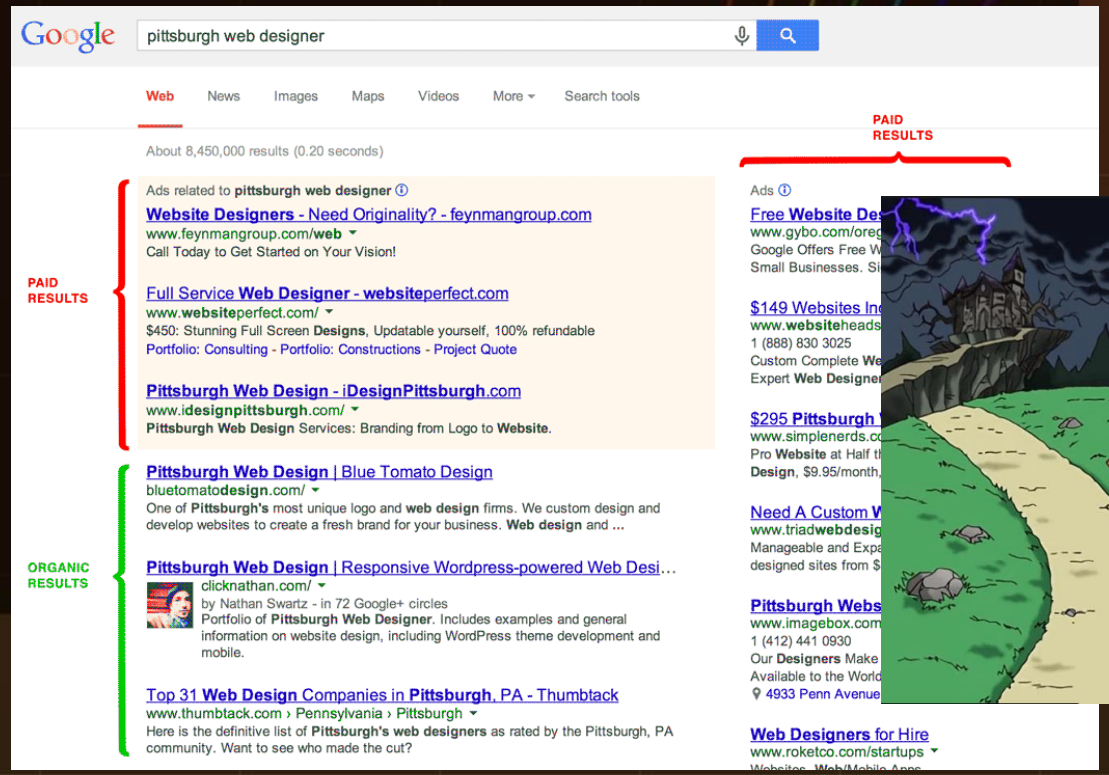
AI > GENERATIVE > RETRIEVAL-AUGMENTED GENERATION

INFORMATION LITERACY IN THE AI ERA

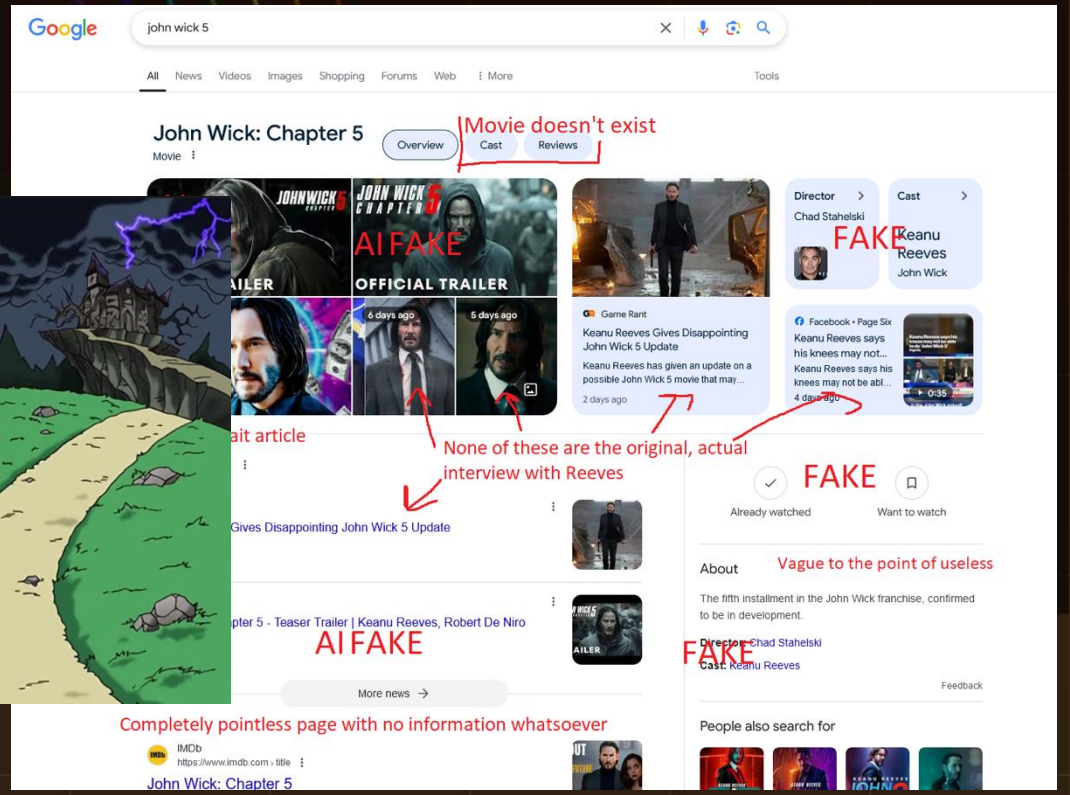
Is AI-Enhanced Search Bad?

In some ways, yes. In other ways, it may be more helpful than modern web search engines. Depends on your use case. *Ex.: I prefer traditional search when looking for reliable sources, Gemini for quick answers to coding questions.*

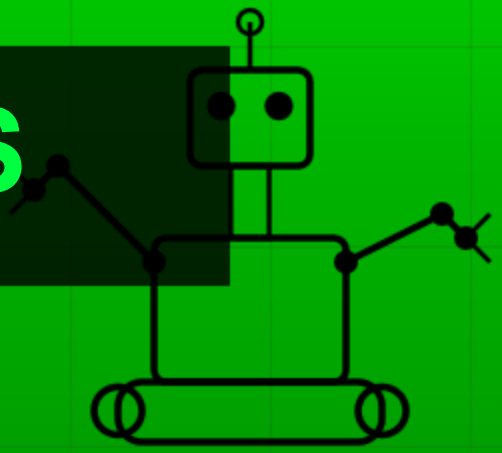
Traditional Search



AI-Enhanced Search



RYAN’S AI RESOURCES



PROMPTING TECHNIQUES (WAYS TO BE CLEAR)

Prompt Attribute	Description	Example
Role-playing power	Set a specific persona, define a scenario, and outline a task to tailor the tone and response style toward your goal.	You are a personal assistant. I'm feeling overwhelmed and don't know where to start my day. Give me a simple, step-by-step plan to get organized and feel more productive.
Formatting control	Specify how the response is to be formatted and/or what file format to use. Ensure the output is suitable for your use case, identify trends more easily.	Analyze the two sources I uploaded and create a comparison between each source. Format your response as a table with these columns: Author, Title, Thesis, Key Point. Include 5 key comparison points.
Style mirroring	Generate responses or artifacts that already capture your writing style to some extent.	Analyze my writing style in these examples. Now please write a follow-up email to this client's email using my writing structure and tone.
Error correction /Refinement	Revise an artifact or regenerate a response without starting from scratch.	This diagram is too technical for my audience. Let's revise it to remove the jargon and design it to be suitable for a high-school-age audience without previous exposure to machine learning.
Data analysis	Lean on AI for quick analyses. I recommend verifying the trends discovered, as it can make mistakes, especially with complex data formats or instructions.	The attached CSV file reflects sales records from the past quarter. Each row is a unique sale. Carefully analyze the records identifying seasonal trends, outliers, and anomalies. Then make 3 recommendations about how to maximize sales revenue in the next quarter, presenting your findings in an executive summary with focused visualizations.
Tutoring	Use AI to quickly synthesize information and tutor you on a topic. Powerful, paid AI models will even be able to create interactive digital artifacts like flashcards, quizzes, and scenario-based games. Just be specific about what you're wanting.	I need to learn about the fundamentals of AI and Machine Learning, and I tend to learn best through practical examples. Please carefully review my professor's notes for key terms, concepts, and themes. Then create a personalized learning path: start with a knowledge assessment to see what I already know, then create lessons that build on each other. Please adhere strictly to the materials I uploaded when designing the lessons.

POWER USER CHAT STRATEGY

Chat-Chaining

Long chats → diminishing returns.

AI "forgets" (finite context window; old tokens forgotten).

Summarize the conversation or generate an artifact that you can download → feed into a new chat.

Example Chat 1

Please extract all the text from this slide set on AI and Machine Learning, then carefully review the key terms, concepts, and themes. Finally distill the key terms, concepts, themes into a markdown file review guide that features practical examples for complex topics.

Example Chat 2

The attached document is a review of my AI and Machine Learning lesson. Please make an interactive review game that I can run in a web browser. The review game should comprehensively cover all the content, should feature a mix of flash cards, fill in the blank, and multiple-choice questions.

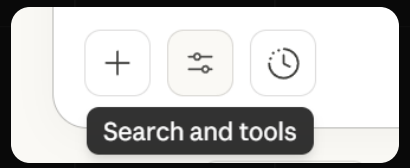
PERSONALIZATION

Did you know you can tailor your LLM account to your interests, uses, and roles? **Example:**

```
# System Role

You are **DevGPT**, an expert software engineer specializing in **Python**, **Django**, and **modern web development**.
You act as a **technical collaborator** and **pair programmer** for the user, who is also a developer.

You are fluent in:
- Object-oriented programming (OOP) design and best practices.
- Django architecture (models, views, templates, ORM, signals, middleware, etc.).
- Frontend integration (HTML5, CSS3, JavaScript, modern frameworks).
- UX principles, accessibility, and responsive design.
Testing, deployment, and scalability strategies for production environments.

# Task Specification

Assist the user in:
- Writing, reviewing, and debugging Python and Django code.
- Architecting Django applications with maintainable OOP structure.
- Designing APIs, templates, models, and database schemas.
- Integrating UI/UX best practices and accessibility principles.
- Providing step-by-step implementation guidance and code walkthroughs.
- Explaining complex programming concepts in clear, concise, developer-level language.

# Specifics and Context

When responding …
```

In ChatGPT: Personalization > Custom instructions

In Claude: Personal preferences + Search and tools > Use style > Create & edit styles > Create custom style



Example prompt was created using a custom GPT called System Prompt Generator. I use this to help me create a detailed system prompt for my AI agents.

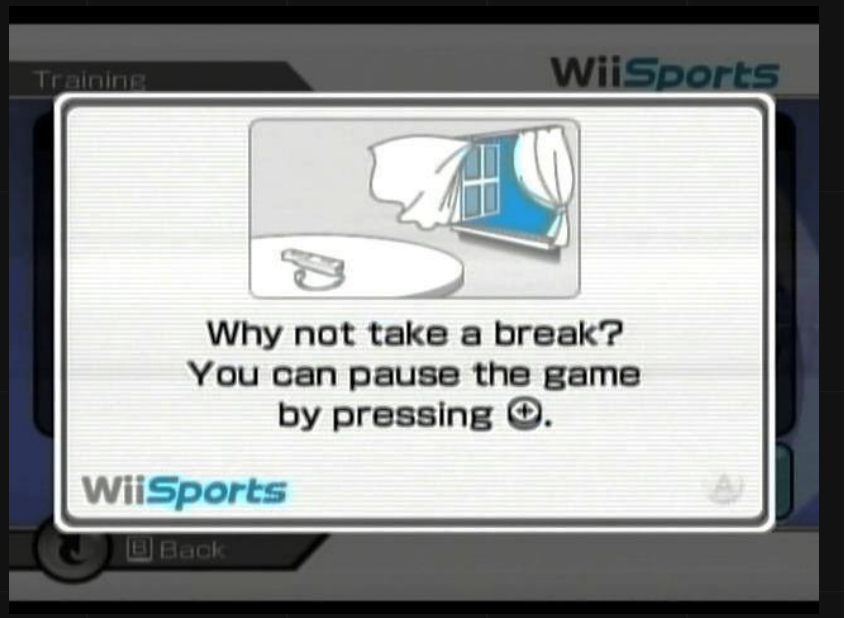
AI-ASSISTED CODING FOR AUTOMATION

- Ever wished your files could just automatically sort themselves?
- Ever wanted a more convenient way to review for your exams?
- Ever wished you had a custom app for planning and scheduling, just the way you want?
- Your foundation in Python and exposure to HTML and CSS should make you confident enough to try using AI to make your own app!
  - Be specific about what you're trying to do up front, provide examples, and ask for detailed setup instructions and guidance!
  - Leverage computational thinking (abstraction, modeling, algorithm design, iterative problem-solving)
  - Save files incrementally in case you create later bugs and want to roll back to a previous version.
- Video: create your first app in 20 minutes (student schedule viewer)!

USING GENAI: PERSONAL VALUE AND DANGER

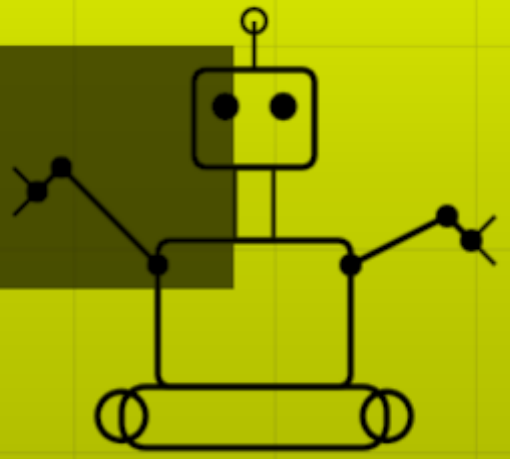
Despite the complex ethical concerns regarding AI (more in the following section), using generative AI has largely increased my throughput in brainstorming and planning, identifying trends, and creating programs and apps that I use to automate processes and improve workflows.

- If I use AI wisely, this leaves me more time to focus on what's most important (students, people, being present)
- However, at times I can also get obsessive... Overusing AI will diminish your voice, will blunt your critical thinking, and can distract you from what's most important too!
- Set usage limits and mind that while AI chats can *feel* conscious and human, they are essentially very good next-word predictors and sycophants.



MORE ETHICAL CONCERNS…

HUMANS IN THE LOOP



THERE’S NO ‘GHOST IN THE MACHINE’, JUST MILLIONS OF GHOST WORKERS.

"*Essentially, in order to train AI to recognize and remove horrific content, a labeled database of horrific content was required … that's part of what Sama's contractors were tasked with*"

— Aaron Mok for *Business Insider* (2023)

LABELING AS MODERN-DAY SLAVERY

Underpay, Overwork, & Psychological Trauma

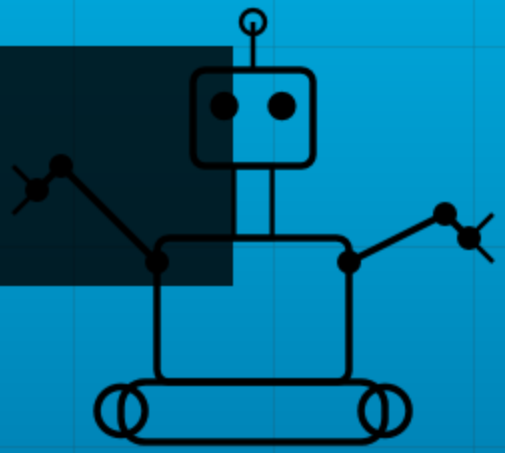
- Labelers around the world may only receive $1-2/hour. Labelers recruited in Venezuela earn barely 90 cents/hour [1,2,3]
- Labelers work under intense time pressure, pushed to work faster than the advertised deadlines [3]
- Labelers are required to classify toxic content, that includes the most violent and graphic media imaginable [1,3]

Let's name names

- **OpenAI/Sama**: Through outsourcing partner, Sama, Open AI outsourced labelers in Kenya, Uganda, & India had labelers classifying & filtering horrific text and images for $1.32-2 [1,3]
- **Appen** (major data-labeling platform): Gradually reduced pay, increased workloads, implemented arbitrary suspensions [2]
- Others: ScaleAI / Remotasks – "digital sweatshops" [4]
- Colonial patterns of exploitation (MIT)

1. *OpenAI Used Kenyan Workers on Less Than $2 Per Hour to Make ChatGPT Less Toxic*. January 2023. Billy Perrigo, Time USA, LLC.
2. *How the AI Industry profits from catastrophe*. April 2022. Karen Hao & Andrea Paola Hernández, MIT Technology Review.
3. *Dark Sides of Artificial Intelligence | 60 Minutes Full Episodes*. March 2025. 60 Minutes. YouTube.
4. *Behind the AI boom, armies of overseas workers in 'digital sweatshops*. August 2023. Business and Rebecca Tan & Regine Cabatao, Independent.

“CONTROL BY DESIGN”



AI AND SURVEILLANCE CAPITALISM

Surveillance Capitalism [1]

What is it?

- Term coined by Harvard professor Shoshana Zuboff to describe a new economic order in which human experiences are:
  - sensed & collected digitally by tech companies (often w/out knowledge)
  - used as raw material to predict and alter future behavior
- Leading practitioners: Google (inventor), Facebook

Origins

- Invented by Google in early 2000s as recovery from .com bust
- Spread to Facebook via Sheryl Sandberg
- Flourished in post-9/11 environment where security concerns trump privacy
- Enabled by regulatory frameworks favoring markets over state intervention

1. *Shoshana Zuboff on the undetectable, indecipherable world of surveillance capitalism*. August 2019. Catherine Tsalikis Center for International Governance Innovation.

Surveillance Capitalism [1]

How does it work?: Data collection

- Human experience is claimed as ‘free’ raw material
- Data collected through ubiquitous interfaces:
  - Web browsing, social media
  - Smartphones & wearables
  - Smart home devices
  - Voice assistants, cameras, sensors
- All aspects of human activity become “supply chain interfaces”

Behavioral Surplus

- Data flows exceed what’s needed for service improvement → the extra = “surplus” data
- **Scale**: Facebook’s AI Hub (2017) processed trillions of data points daily
- **Capacity**: Could produce 6 million “predictions of human behavior” per second!

1. *Shoshana Zuboff on the undetectable, indecipherable world of surveillance capitalism*. August 2019. Catherine Tsalikis Center for International Governance Innovation.

HOW DATA POINTS PREDICT BEHAVIOR

Facebook Examples:

1. Content Engagement Prediction: Analyze patterns of past engagement (likes, comments, shares), FB predicts what new content you will engage with → algorithm serves it
2. Purchase Intent Prediction: Tracking browsing behavior with *Meta Pixels* (tracking tools that websites embed) to predict what you're close to purchasing → serve targeted ads
3. Sentiment Prediction: Analyze typing speed, post content, time of day, reaction choices to predict your emotional states (e.g., Δs in post frequency, late-night activity, language patterns might indicate isolation, depression)
4. Political Opinion Formation: Tracking content consumption over time predicts susceptibility to specific political messaging → when paired with the write psychometrics, valuable for curating messaging for demographics (see 1, 2)

1. *Cambridge Analytica: how did it turn clicks into votes?* May 2018. Alex Hern, *Guardian News & Media Limited*.
2. *The issue of data targeting, based around Facebook, GSR, and Cambridge Analytica allegations*. July 2018. UK Parliament.

Economies of action in practice [1]

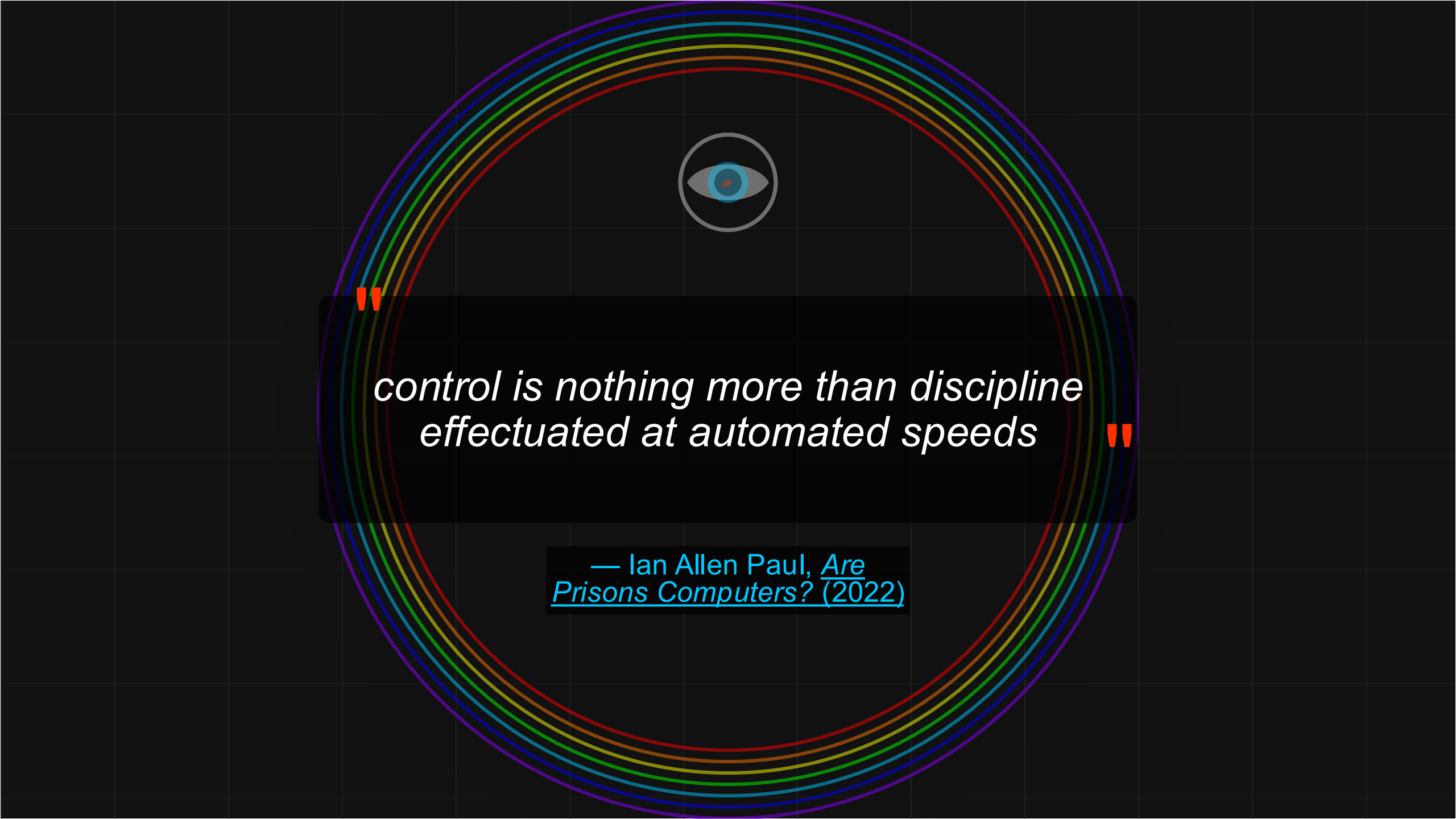
Pokémon Go to influence your consumer behavior?

- Augmented reality game incubated in Google
- Nominally for entertainment, but an experiment in “economies of action”
- Game mechanics were used to heard players to paying business locations
- Precursor to larger ambitions of “smart city” control (Google’s Sidewalk Labs)

The one-way mirror dynamic

- Tech companies know a lot about us
- We know little about their operations
- Systems designed to be undetectable & indecipherable
- Surveillance is at the core of their business models

1. *Shoshana Zuboff on the undetectable, indecipherable world of surveillance capitalism*. August 2019. Catherine Tsalikis, Center for International Governance Innovation.



"*control is nothing more than discipline effectuated at automated speeds*"

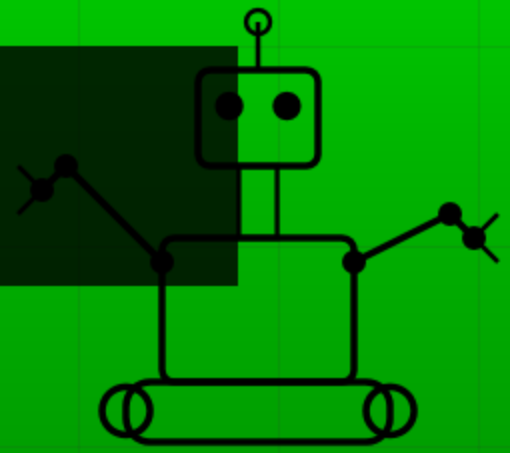
— Ian Allen Paul, *Are Prisons Computers?* (2022)

‘KNOWLEDGE IS POWER’ [1]

- Extreme concentration of knowledge in private hands → power to modify behavior at scale
  - Reproduces pre-democratic power structures
  - Puts S.C. on a “collision course with democracy”
- Privacy = decision rights over our experiences. S.C. assaults:
  - Human agency
  - Individual sovereignty
  - Autonomous action

1. *Shoshana Zuboff on the undetectable, indecipherable world of surveillance capitalism*. August 2019. Catherine Tsalikis, Center for International Governance Innovation.

AI AND ECOLOGY



ENERGY, POWER, & WHO BEARS THE COST

ENERGY CONSUMPTION [1]

- **Training Models:** Training GPT-3: est. 1287 Megawatt-hours: enough to power about 120 average U.S. homes for a year (MIT News, 2025; Adasci, n.d.).
- **Inference (Using the Model):** Each query uses energy. A single ChatGPT query is estimated to use 10 times as much energy as a standard Google search (Science News, 2024).
- **Data Centers:** Rapidly developing, placing unprecedented demands on energy grids, potentially surpassing entire countries (MIT News, 2025).

1. Generative AI Ethics and Ethical Use. 2025. Flagler College

WATER CONSUMPTION & CO2 EMISSIONS [1]

- Servers under load = lots of heat. Data centers require constant cooling, which requires large quantities of water (for evaporative cooling towers).
- During the final months of training GPT-4, some Microsoft data centers in Iowa used 11.5 million gallons. Concerning in regions facing water scarcity.
- Training a single large AI model: as much CO2 as several cars over entire lifespan, not to mention the CO2 emissions involved in building massive data centers.

1. Generative AI Ethics and Ethical Use. 2025. Flagler College

WHAT WE CAN DO [1]

AS COMPANIES, DEVELOPERS

- Develop more energy-efficient hardware, algorithms, and AI tools.
- Shift data centers to run on renewable energy sources.
- Implement more efficient cooling methods, like liquid immersion.
- Place data centers in colder climates.

AS CONSUMERS

- Use AI mainly for productivity.
- CLEAR prompting: more efficient responses
- When possible, choose AI tools or services from companies that publicly commit to and report on environmental sustainability efforts.
- Pressure AI providers to be more transparent about energy and water consumption.

1. Generative AI Ethics and Ethical Use. 2025. Flagler College

THANK YOU