

# AI/ML Fundamentals for Product Managers

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# Todays Agenda

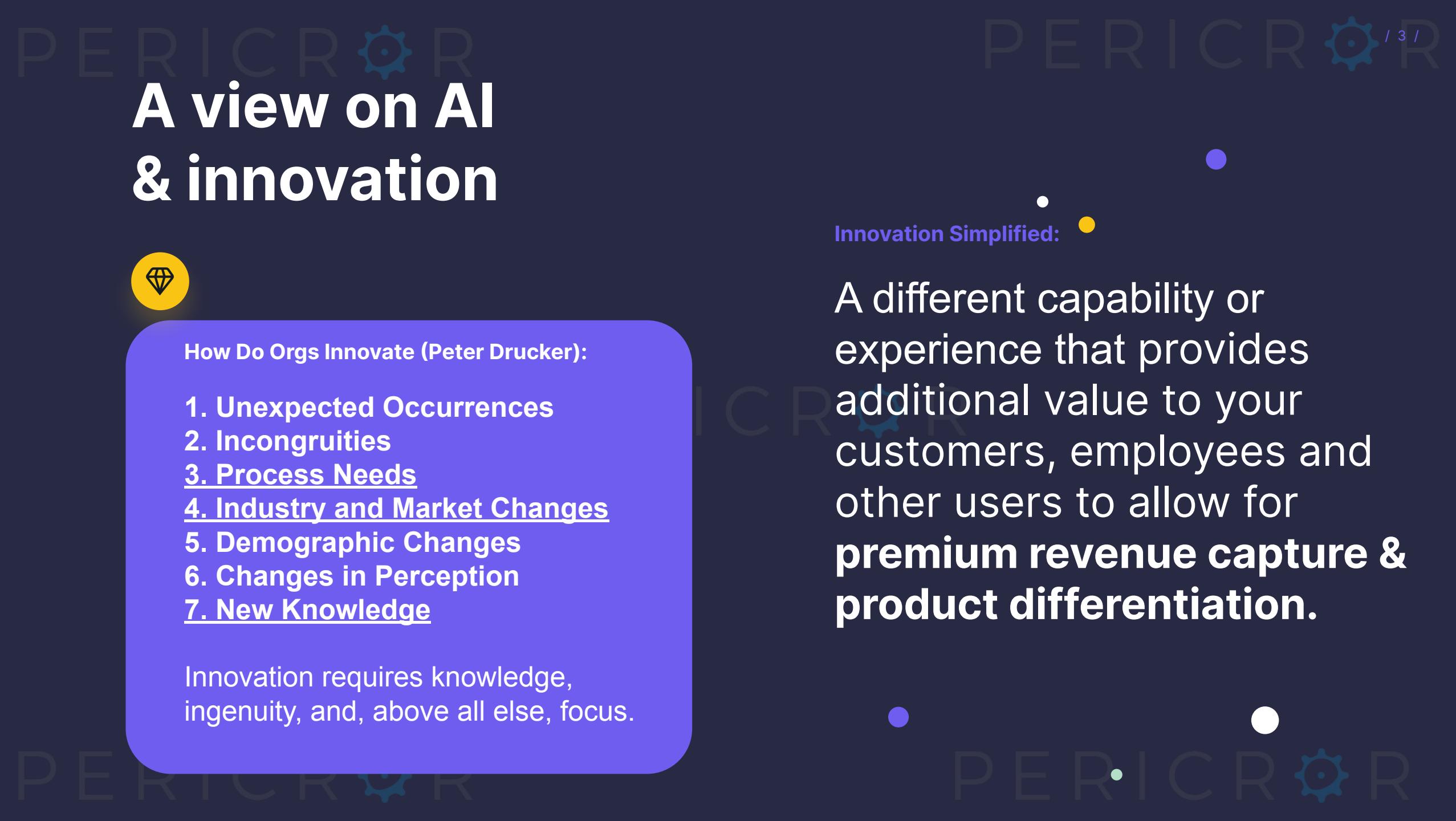


A brief overview of AI/ML for product managers to become familiar with using AI in their products, covering:

- Why Learn AI?
- How might you Operationalize AI?
- What Capabilities are in AI?
- How does AI Work?

As a product manager, it is important to learn AI and machine learning skills for several reasons:

- **Understand modern tech capabilities of AI and machine learning**
- **Ability to work with developers on AI**
- **Stay competitive & maximize revenue**
- **Improve decision-making & productivity**
- **Enhance customer experience & value**



# A view on AI & innovation



How Do Orgs Innovate (Peter Drucker):

1. Unexpected Occurrences
2. Incongruities
3. Process Needs
4. Industry and Market Changes
5. Demographic Changes
6. Changes in Perception
7. New Knowledge

Innovation requires knowledge, ingenuity, and, above all else, focus.

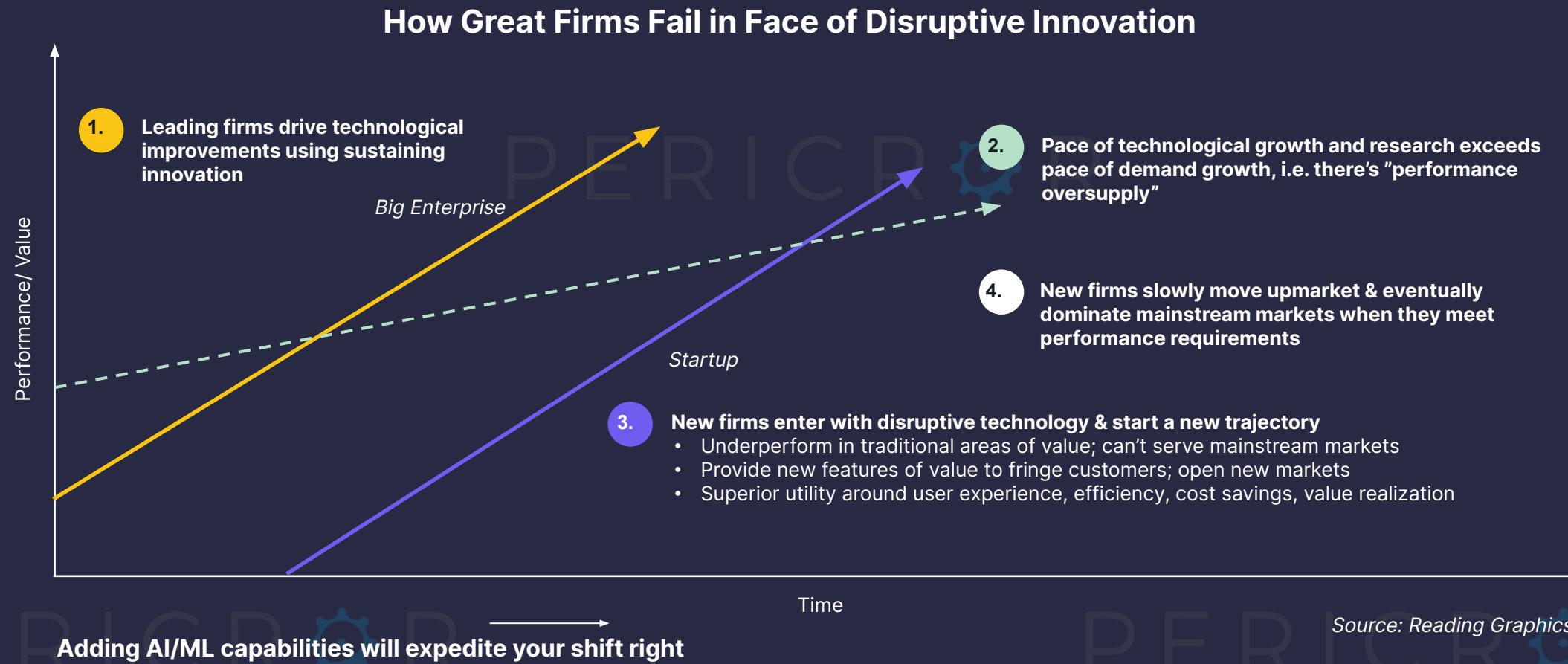
Innovation Simplified:

- A different capability or experience that provides additional value to your customers, employees and other users to allow for **premium revenue capture & product differentiation**.
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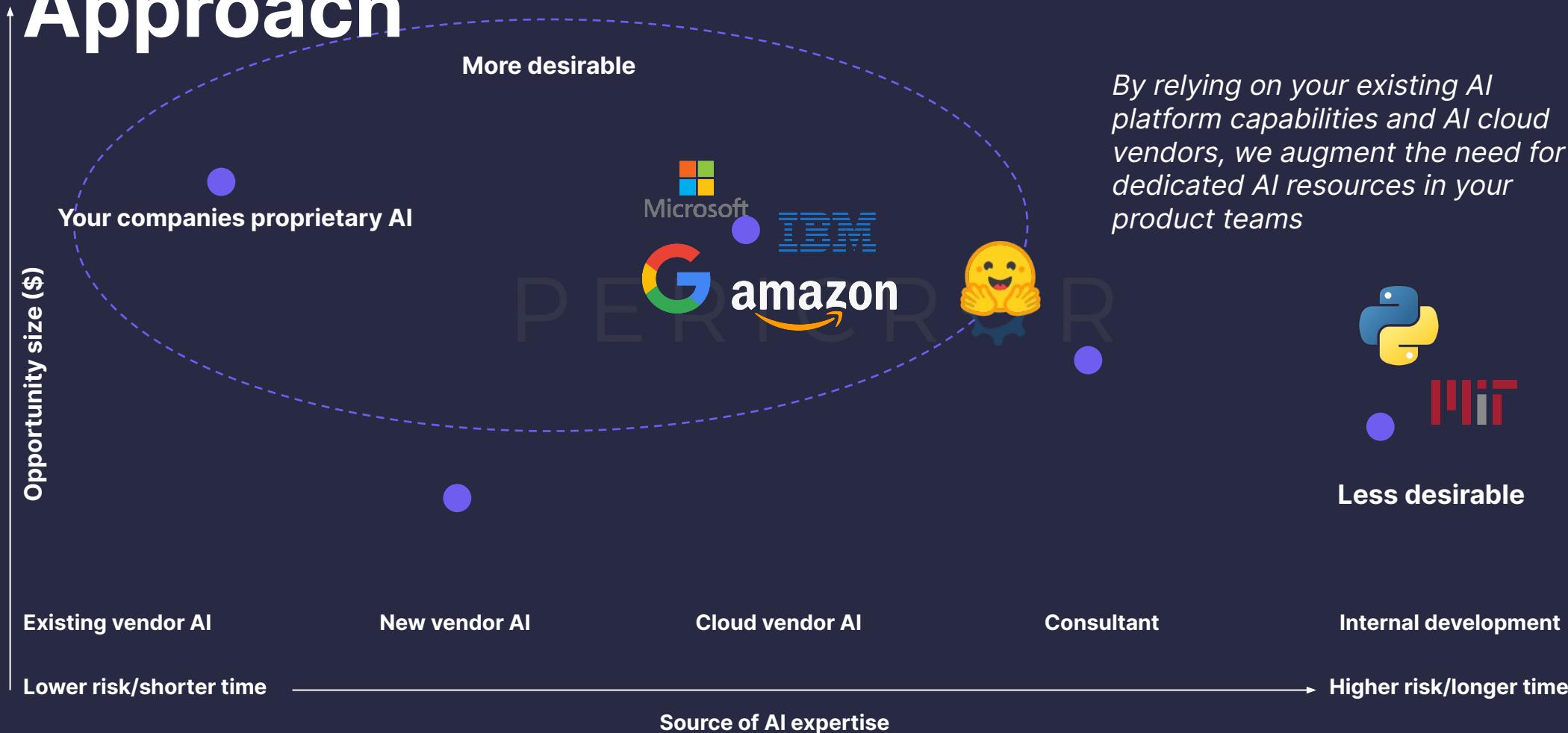
# Why learn & incorporate AI?

# The Innovator's Dilemma

Because leading firms consciously (a) listen to today's needs of their customers and (b) focus their investments on innovations with quick payback, they tend not to explore disruptive tech that improves UX & value until that new tech becomes the norm.



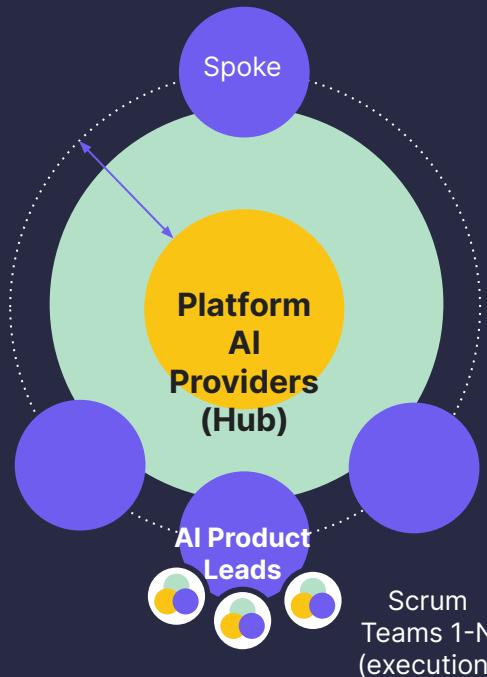
# Your AI Technology Approach



# Recommended AI Product Organizational Structure

## Governing coalition

A team of business, IT, and analytics leaders that share accountability for the AI transformation



### Hub

A central group headed by a C-level analytics executive who aligns strategy

#### Responsibilities

- Talent recruitment and training strategy
- Performance management
- Partnerships with providers of data and AI services and software
- AI standards, processes, policies

### Gray area

Work that could be owned by the hub or spokes or shared with IT

#### Responsibilities

- Project direction, delivery, change management
- Data architecture, data strategy, code development
- User experience
- IT infrastructure
- Organizational capability assessment, strategy, funding

### Spoke

A business unit, function, or geography, which assigns a manager to be the AI product owner and a business analyst to assist him or her

#### Responsibilities

- Oversight of execution teams
- Solution adoption
- Performance tracking

### Execution team

Assembled from the hub, spoke, and gray area for the duration of the project

### Key roles

#### HUB:

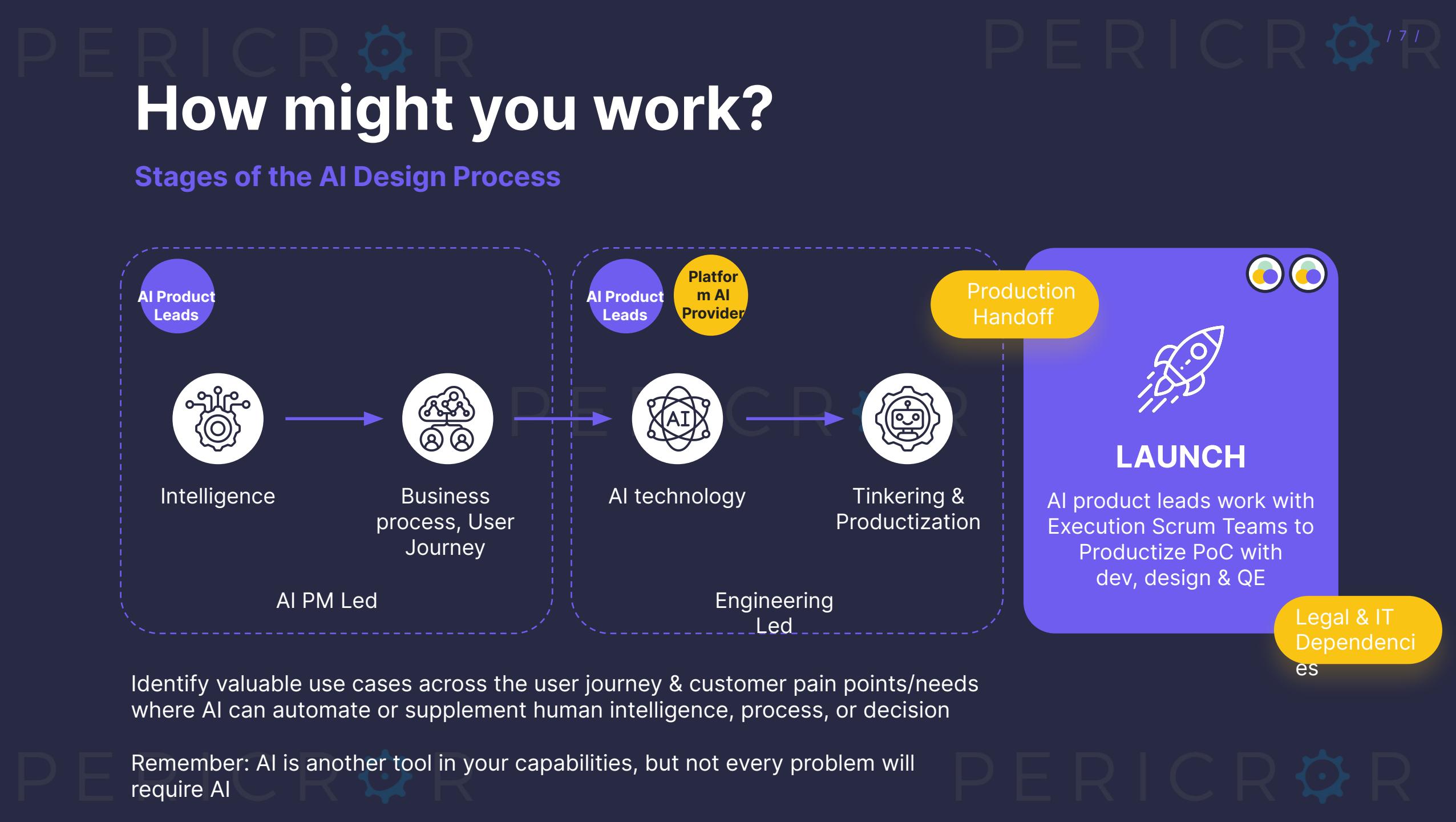
- Data scientist
- Platform developer
- UI designer

#### SPOKE:

- Product owner
- Application developer

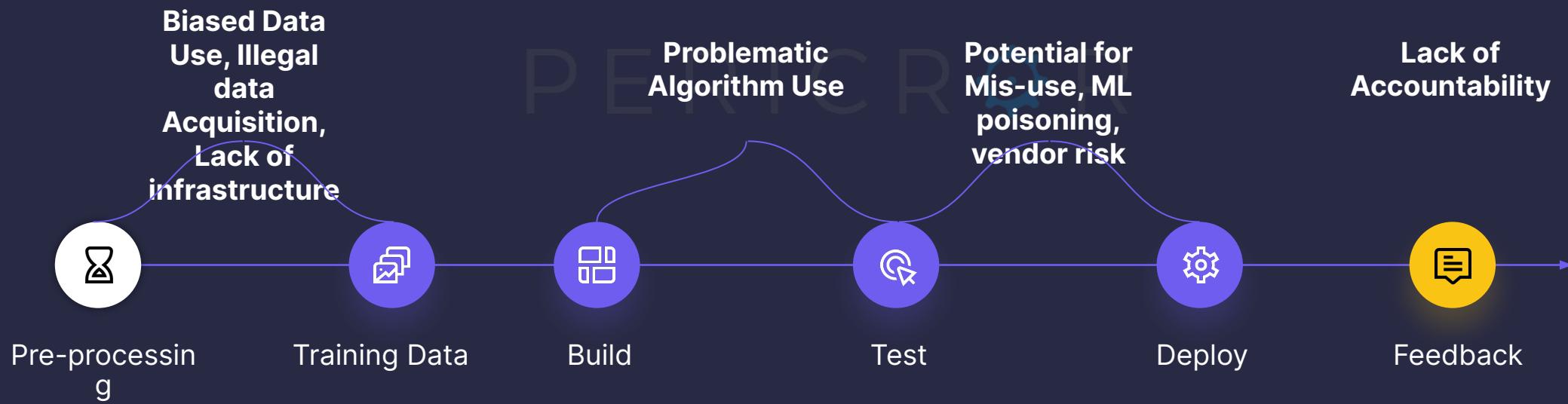
#### EXECUTION TEAM:

- Product Owner
- UI designer
- Application developer



# AI Technology Risks

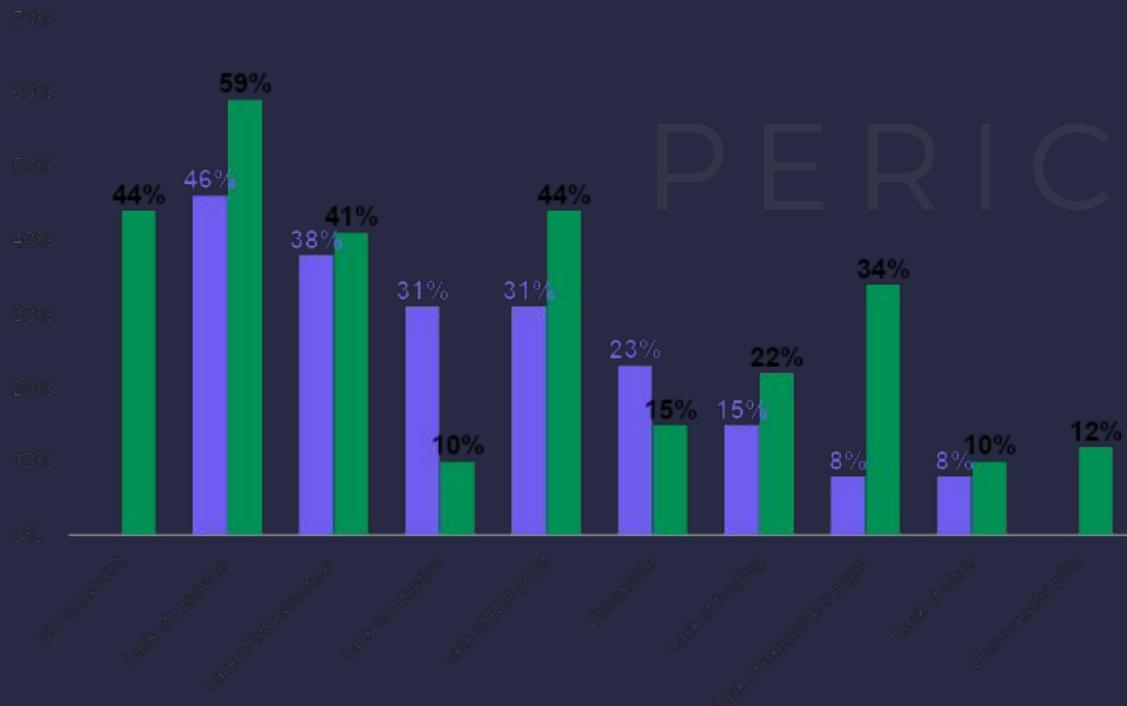
As a PM productizing AI capabilities, it's important to be mindful of Business & Ethics Risks across different Stages of Implementing AI



# PERICOR Business Risks

## Companies Implementing AI

Companies that have actively tried to implement machine learning and AI solutions ran into the following challenges, which begin with lack of executive support



Lack of proven ROI

Lack of executive support

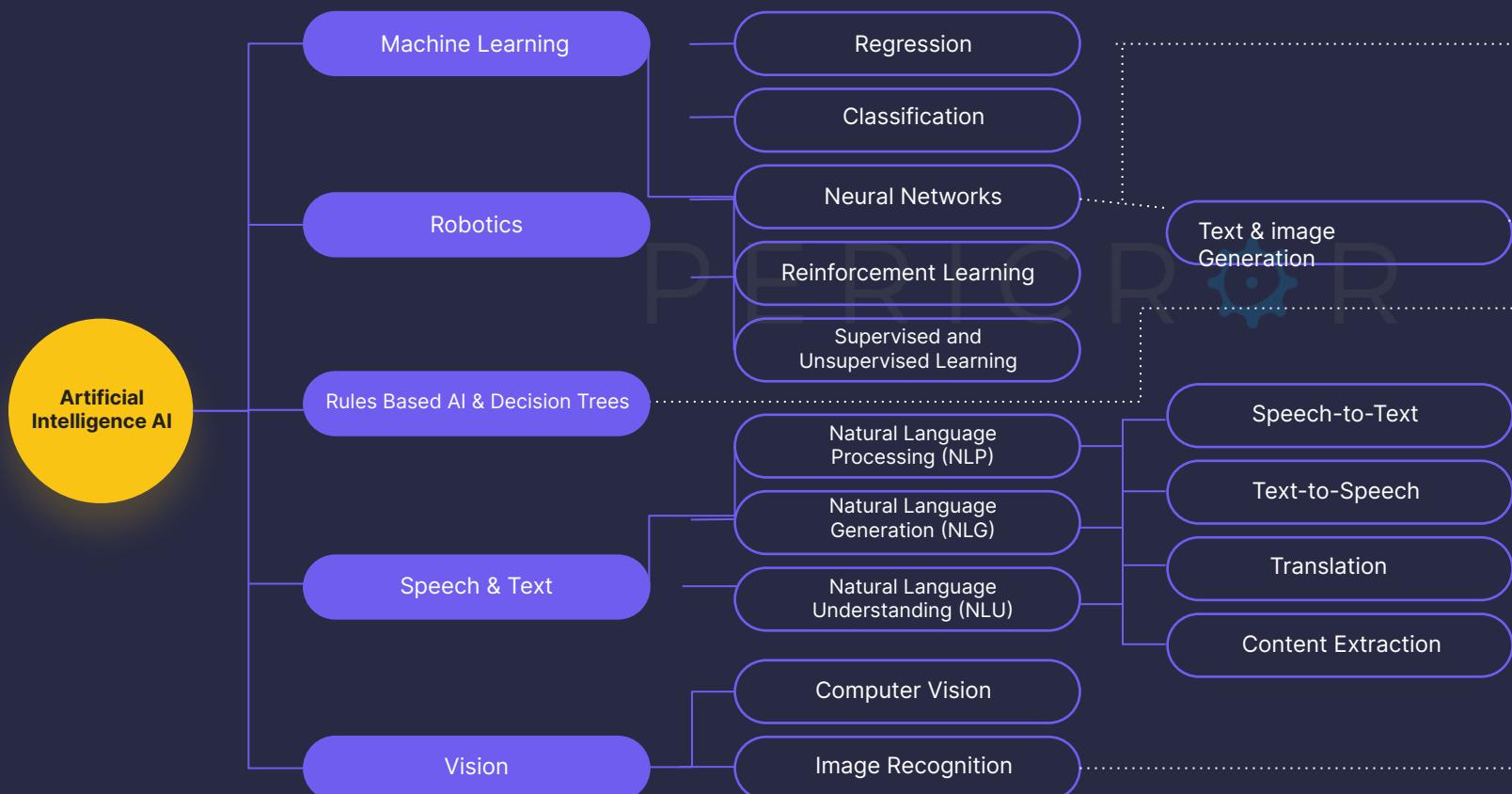
Lack of successful pilot

Lack of funding

Lack of resources

Source: MIT

# What capabilities are in AI Technology?



**Artificial Intelligence** is a broad field of study with dozens of subsections, all ultimately working to make computers perform human tasks.

## NETFLIX

Example: Netflix's Recommendation Engine

## OpenAI

Example: Chat GPT



Example: Automated call centers



Example: Apple's "Siri" or Amazon's "Alexa"



Example: Autonomous (self-driving) Vehicles



# Machine Learning



“ Machine learning is the study of computer algorithms that allow computer programs to automatically improve through experience.

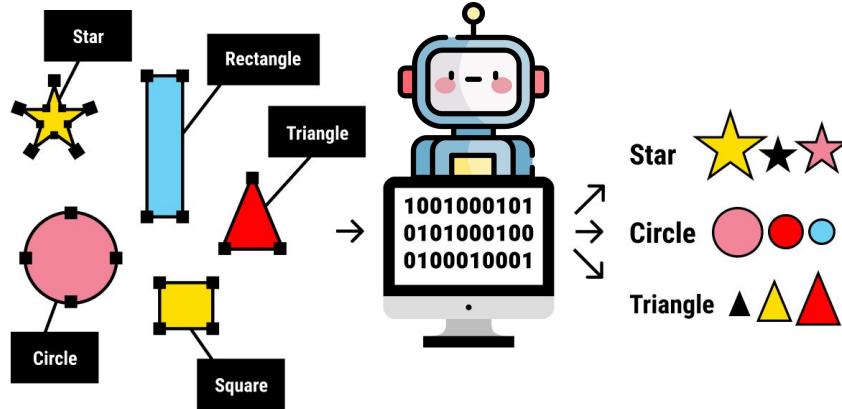
~ Tom Mitchell,  
Machine Learning, McGraw Hill, 1997  
Carnegie Mellon University  
Machine Learning

Used today in:

- Self driving cars to see and classify (identify) stop signs, lanes, people
- Email to detect spam
- Predicting home prices & temperatures
- Teach robots to play games
- Understand and come up with text, images, sounds

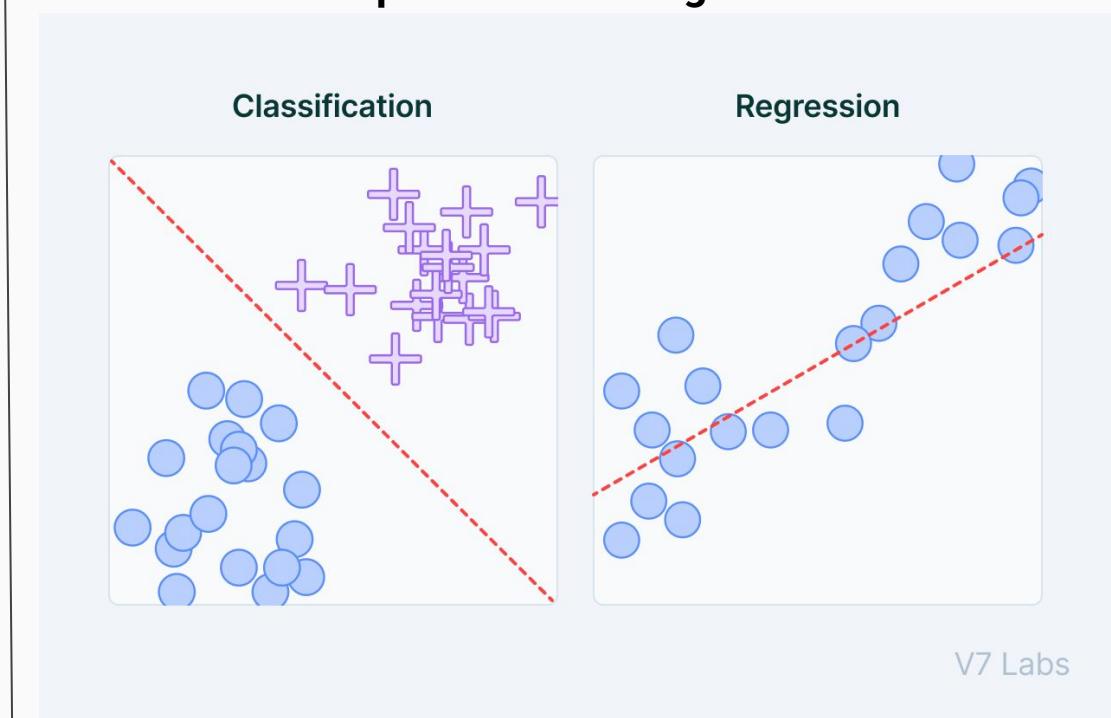
# Common Types of Machine Learning

- **Supervised Learning:** Machine learning where the algorithm is trained on labeled data to predict or map input features to corresponding output labels.



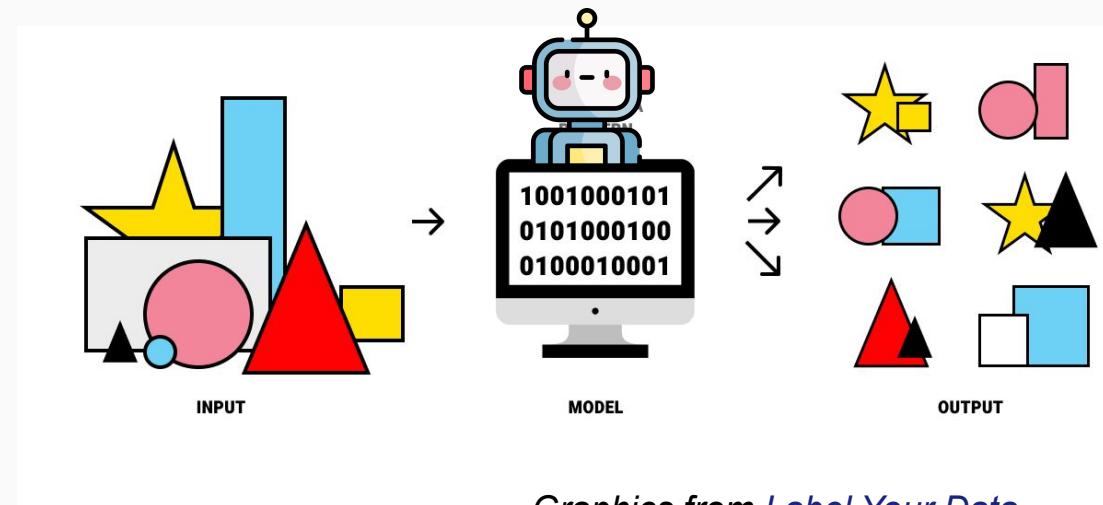
Graphics from [Label Your Data](#)

## Common supervised learning use cases

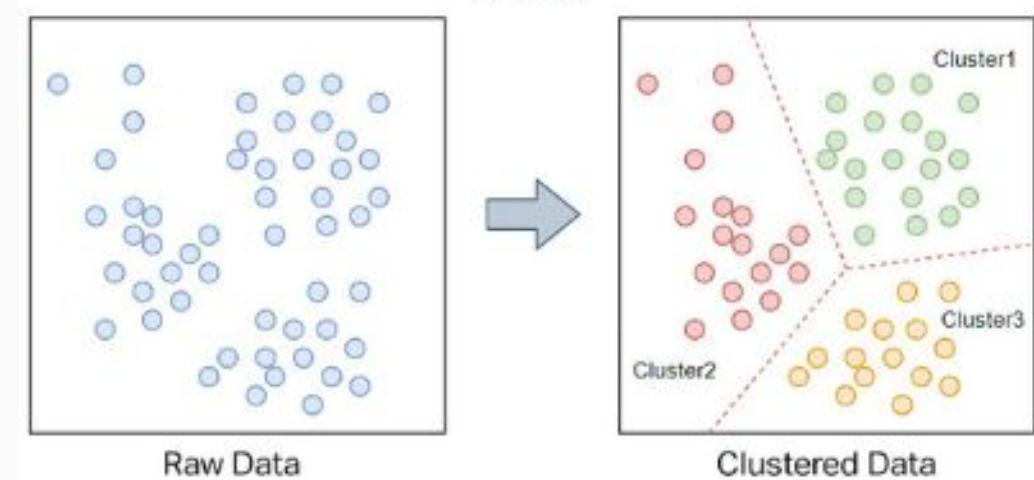


# Common Types of Machine Learning

- **Unsupervised Learning:** Machine learning where the algorithm explores and identifies patterns or structures in unlabeled data without specific guidance.

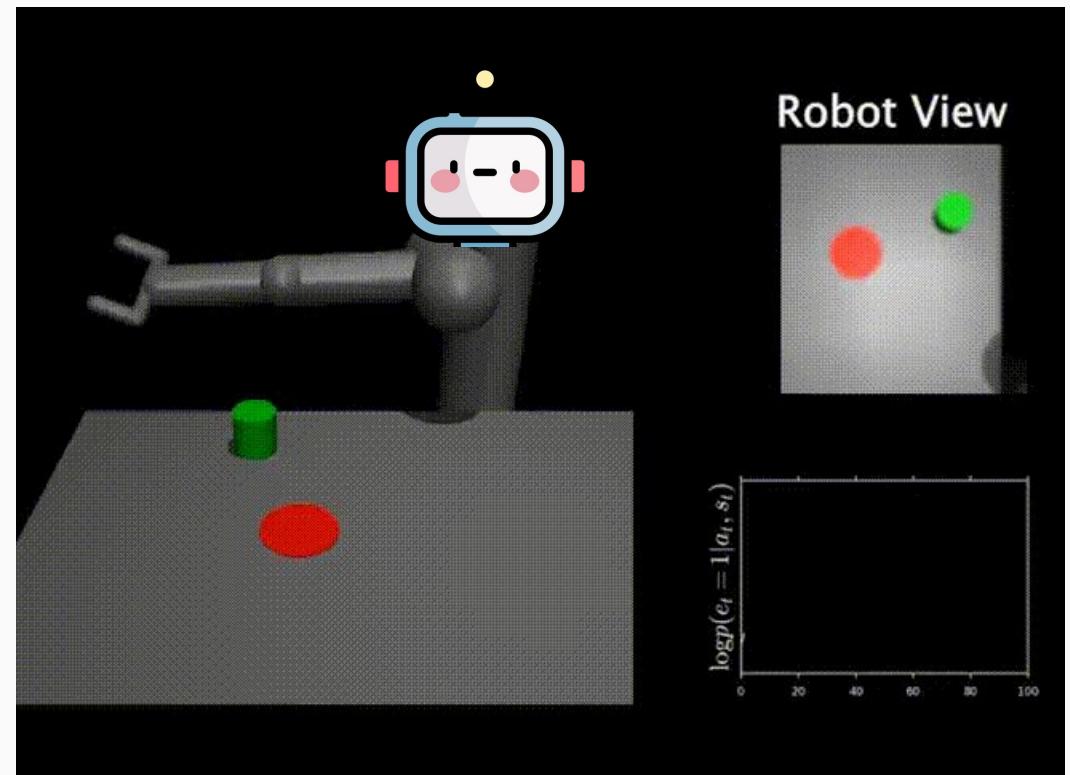


**Common unsupervised learning use case: Clustering**



# Common Types of Machine Learning

- **Reinforcement Learning:** Machine learning where an agent learns to make decisions through trial and error in an environment, receiving feedback in the form of rewards or penalties to improve its actions over time
- A robot can “learn” to move a green cylinder into a red circle by being rewarded if it does
- An **objective function**, such as how close the green cylinder is to the red circle, mathematically encodes how much of a “reward” the robot receives, the closer it gets, the higher the reward!

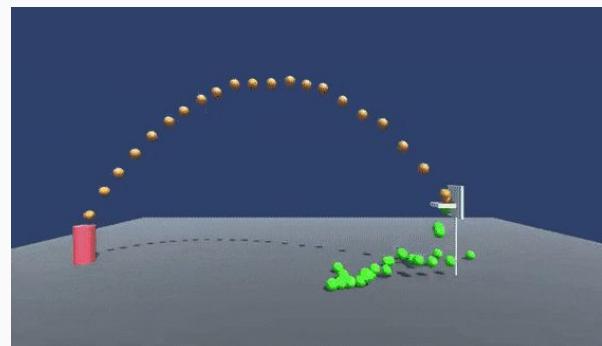


[Berkeley artificial intelligence research](#)

# Two Supervised Machine Learning Examples

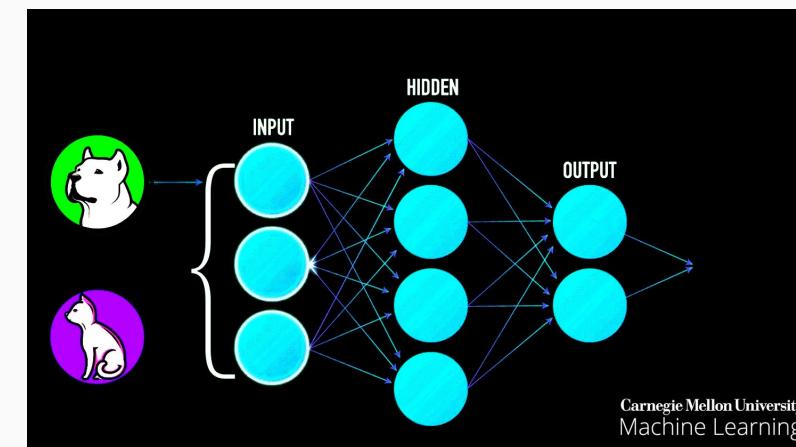
## Prediction

- Given a lot of data and a measure of “correctness”, we can “train” a prediction function
- Basic prediction from a **linear regression** if question is linear & 2 dimensional (x,y)



## Classification

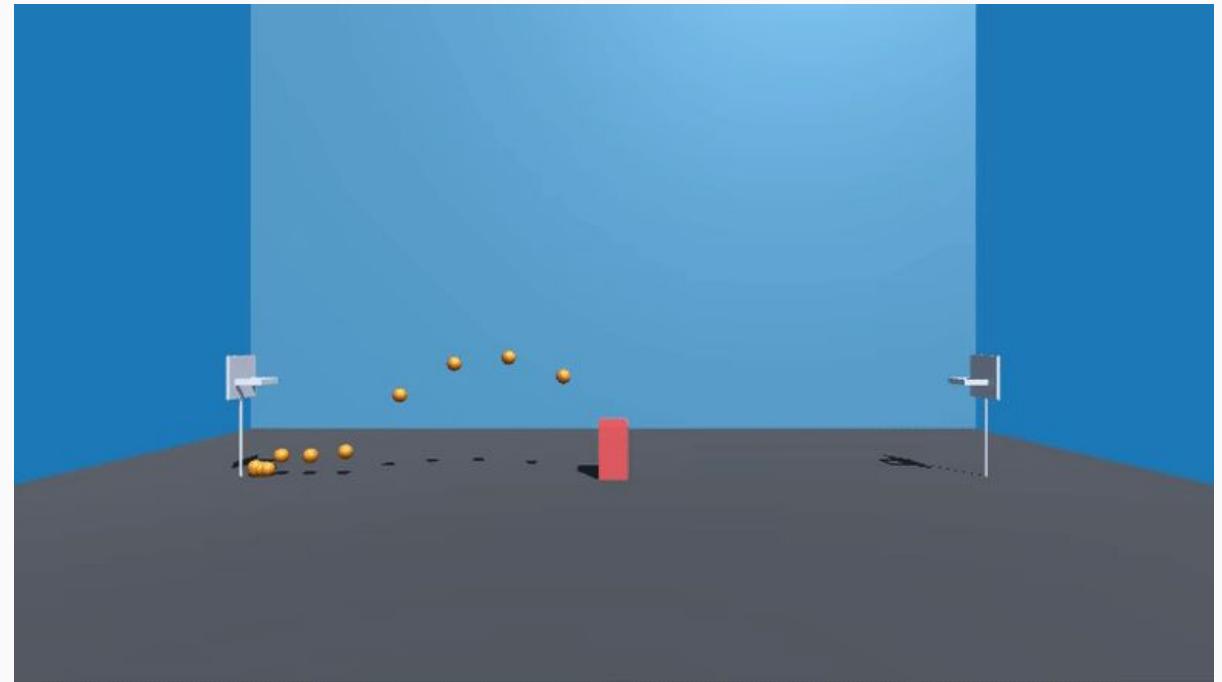
- Given data and a set of unique characteristics, we can classify & recognize different objects
- Basic classification from a **neural network**



# Machine Learning Example: Prediction With Linear Regression

**Consider trying to play basketball using machine learning**

- Rules: If the shooter is X distance away from the hoop, and using a fixed angle, shoot the ball with Y force.
- Goal prediction: What force (Y) should we use for each distance (X) so that the ball goes in the hoop?
- When starting, we have no idea how much force we should use for each distance and miss most shots

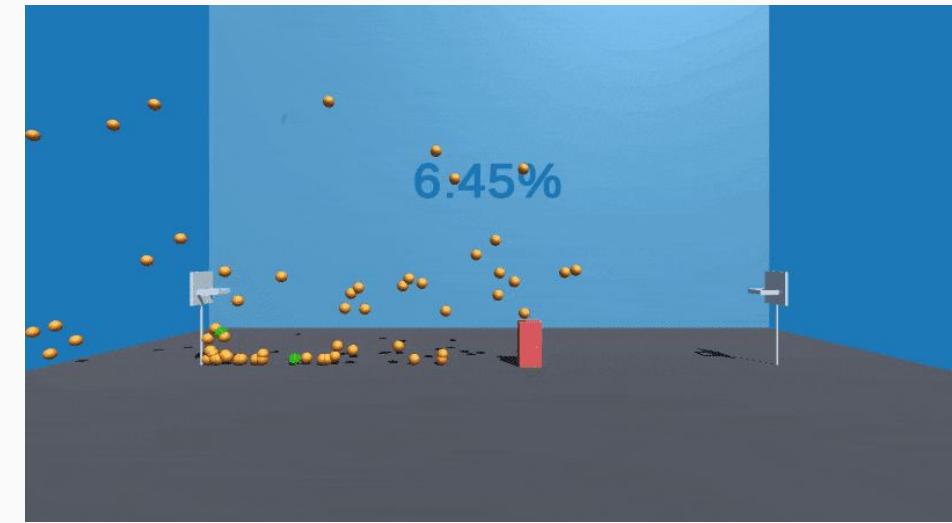


Example from [tensorflow](#)

Slides courtesy of [www.teachkidsrobotics.com](http://www.teachkidsrobotics.com)

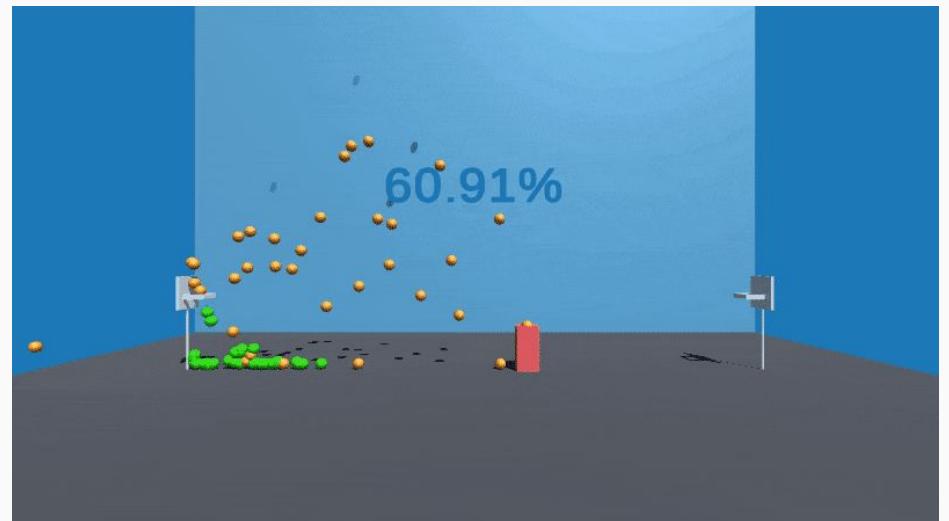
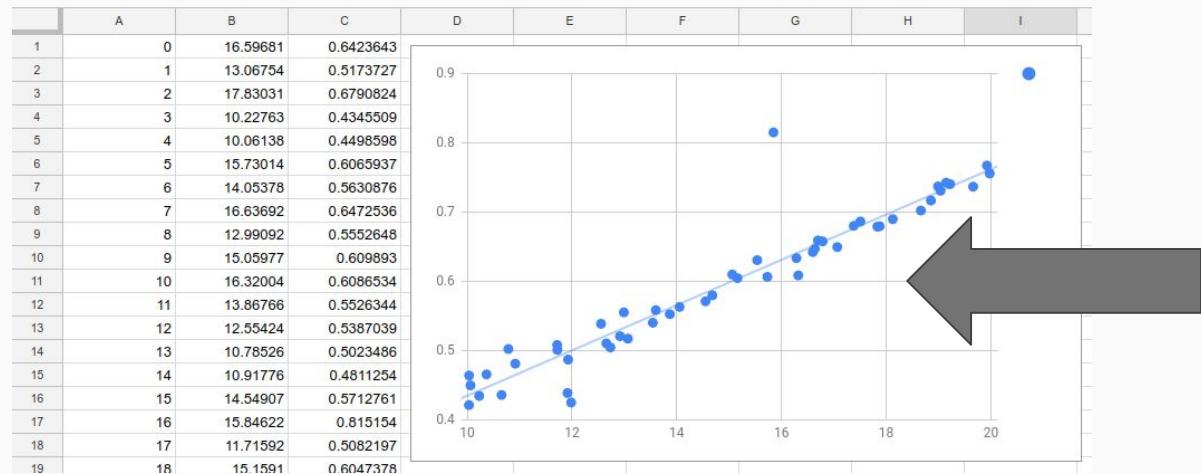
# Machine Learning Example: Prediction with Linear Regression

- We shoot the ball randomly and we “learn” what shot went in the basket by recording force Y at distance X
- With enough shots made, we can use a **linear regression** to predict how much force is needed for any distance!
- Good for problems with a 2D (x/y) representation and linear solution, as a line is represented with the equation  $y=mx+b$ , the linear regression finds the best m and b that gets as close as possible to the points we consider solutions (i.e baskets made). These set of solution points can be thought of as our training data.

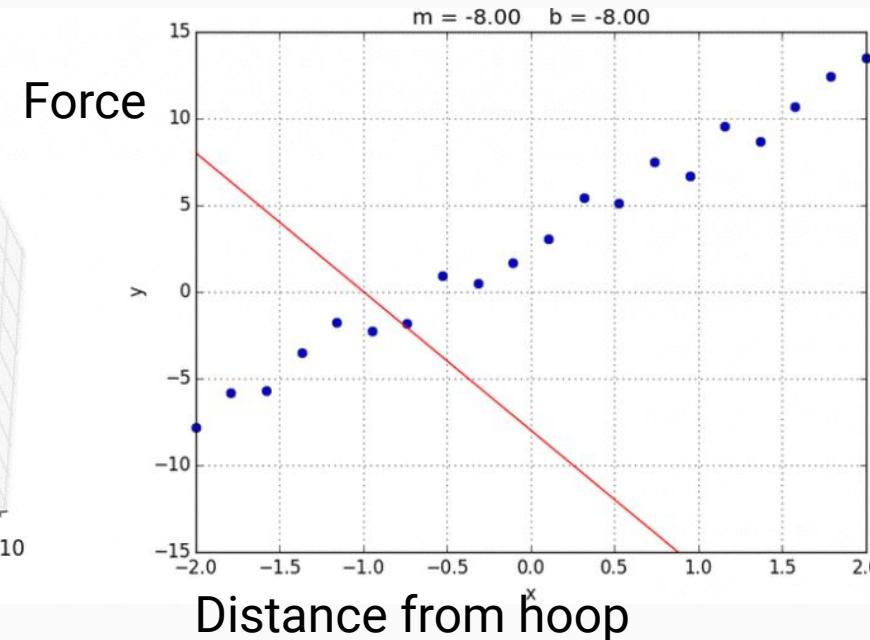
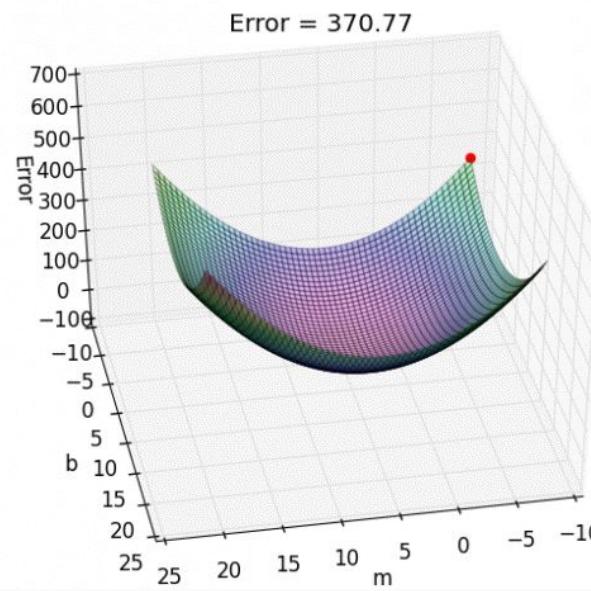


# Machine Learning Example: Prediction with Linear Regression

- Consider graphing all the successful baskets force (y) and distance (x). We would find that most shots fall on a specific line (the “optimal” solution of force for a given distance guaranteed to make the basket)
- The linear regression line finds the solution with points



# Machine Learning Example: Prediction with Linear Regression

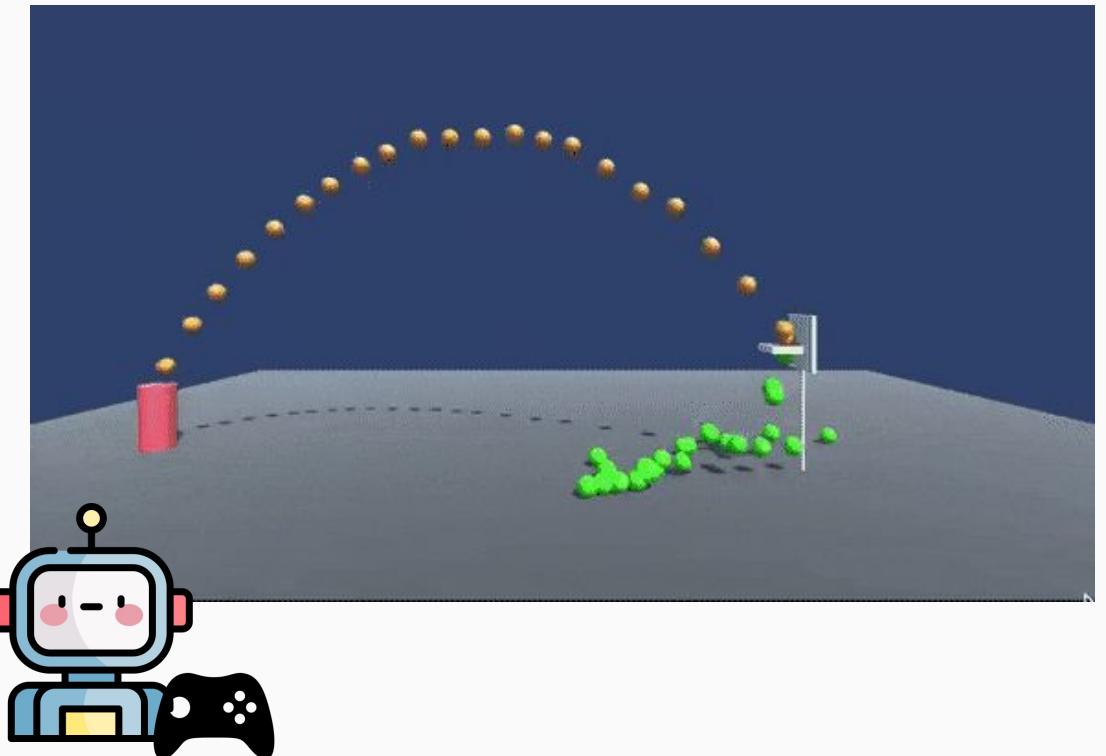


- Visualizing the prediction (red line) over time as error is reduced by recording more baskets distance & force, the linear regression line becomes more accurate / optimal.
- On the left we see the **gradient descent** visualized as we minimize error (misses) by taking more shots. Gradient descent is a way to calculate the 'error' or how far off the prediction was from the actual value. The lower the error, the better.

# Machine Learning Example: Prediction with Linear Regression

## Playing basketball perfectly using machine learning

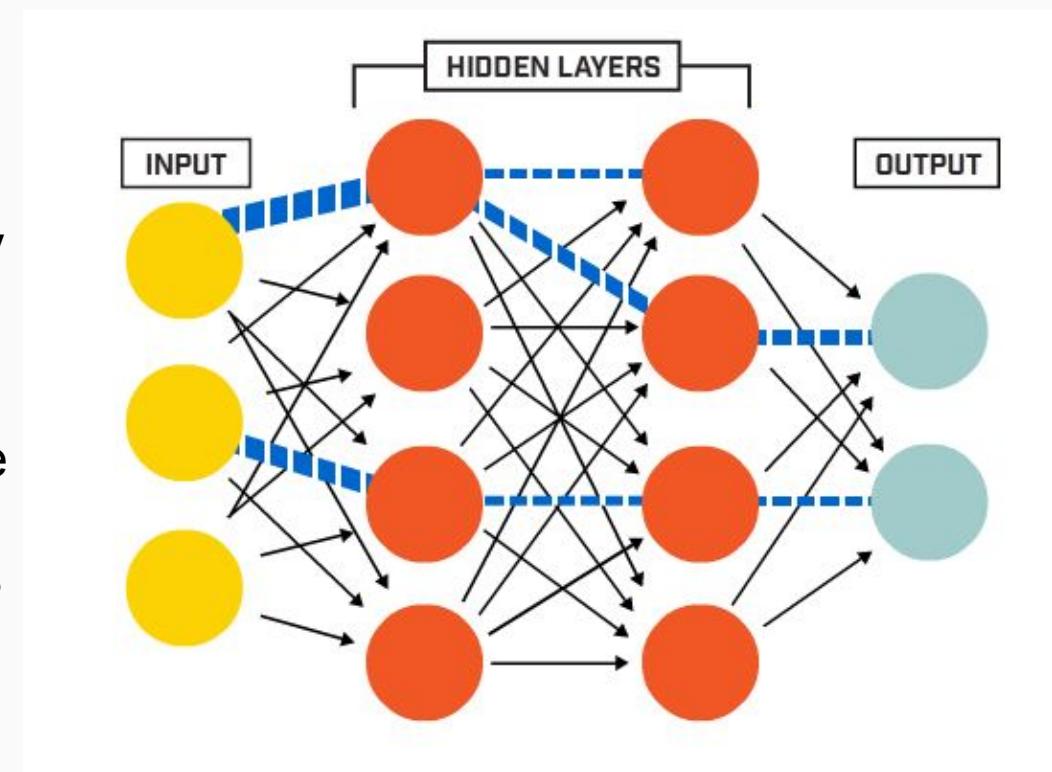
- Once we have enough data, we will have found a line that predicts the proper force (Y) even for distances (X) we had not previously attempted
- With enough data, we were able to interpolate the optimal function that reflects the game physics
- Note this key limitation: basic linear regressions only work for predicting outcomes that can actually be modeled with a linear equation. Other regressions exist for quadratic or logistic functions.



# Machine Learning Example: Classification with Neural Net

## What is a Neural Network?

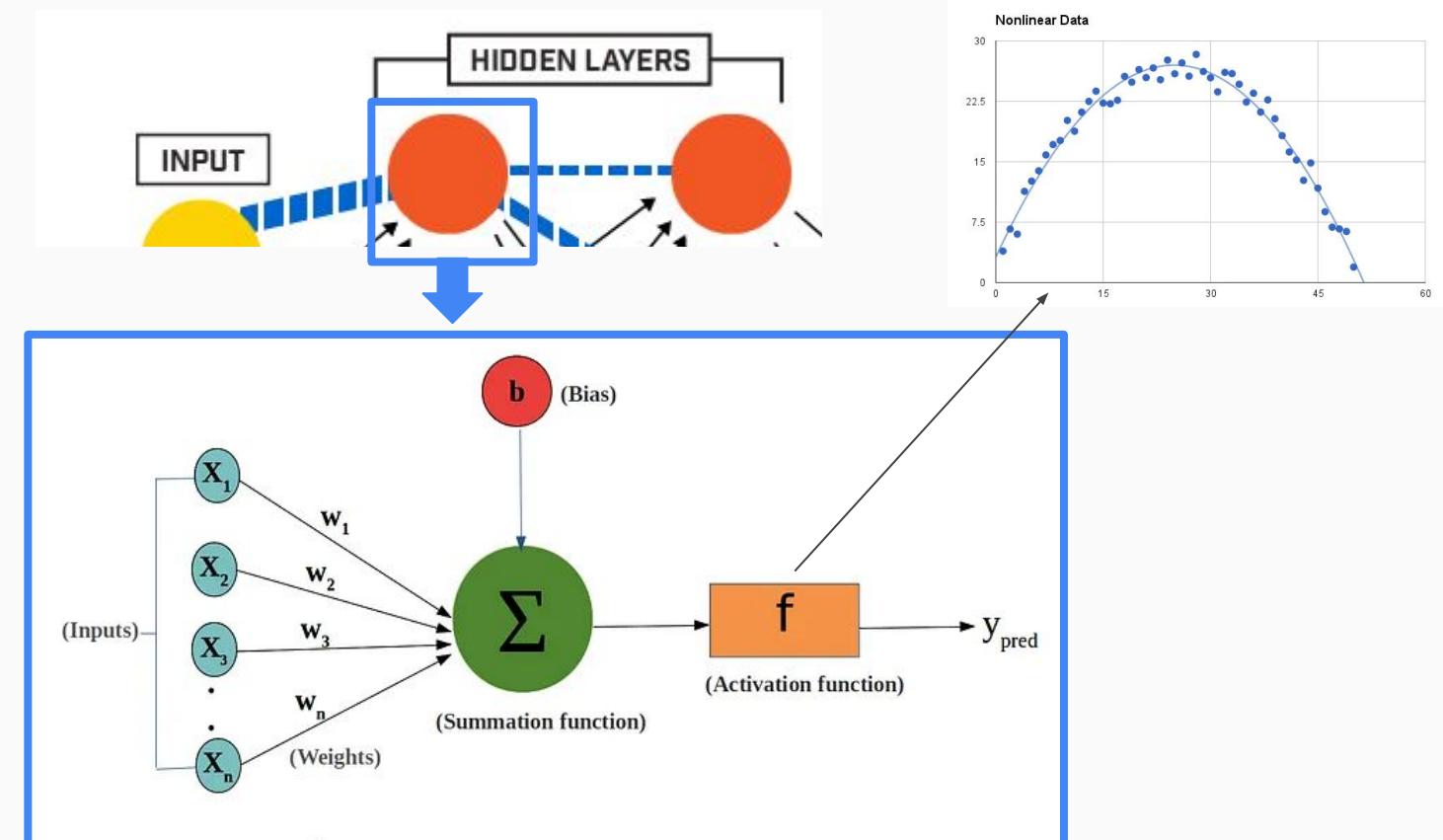
- Teaches computers to process data in a way that is inspired by the human brain's neurons
- A type of machine learning, called deep learning (due to the often large number of layers), that uses interconnected nodes or “neurons” in a layered structure to transform inputs into desired outputs



# Machine Learning Example: Classification with Neural Net

## Neural Network “Neuron” / Node

- Mathematically, a neural network “neuron” accepts some input, that is fed to an **activation function** which then maps the inputs into a new form of possibly nonlinear output
- **Weights** scale the input
- **Bias** offsets the summation
- Activation functions help encode checks for desired dimensions/traits of inputs (sigmoid, relu, softmax)



# Machine learning example: Classification with Neural Net

## Classifying tree vs balloon example

- We classify objects by introducing “dimensions” (variables quantifying one specific feature of the object)
- With enough dimensions, we can accurately distinguish one object from another
- Each dimension could be checked in the hidden layers, the activation of which helps classify objects

## Difference between

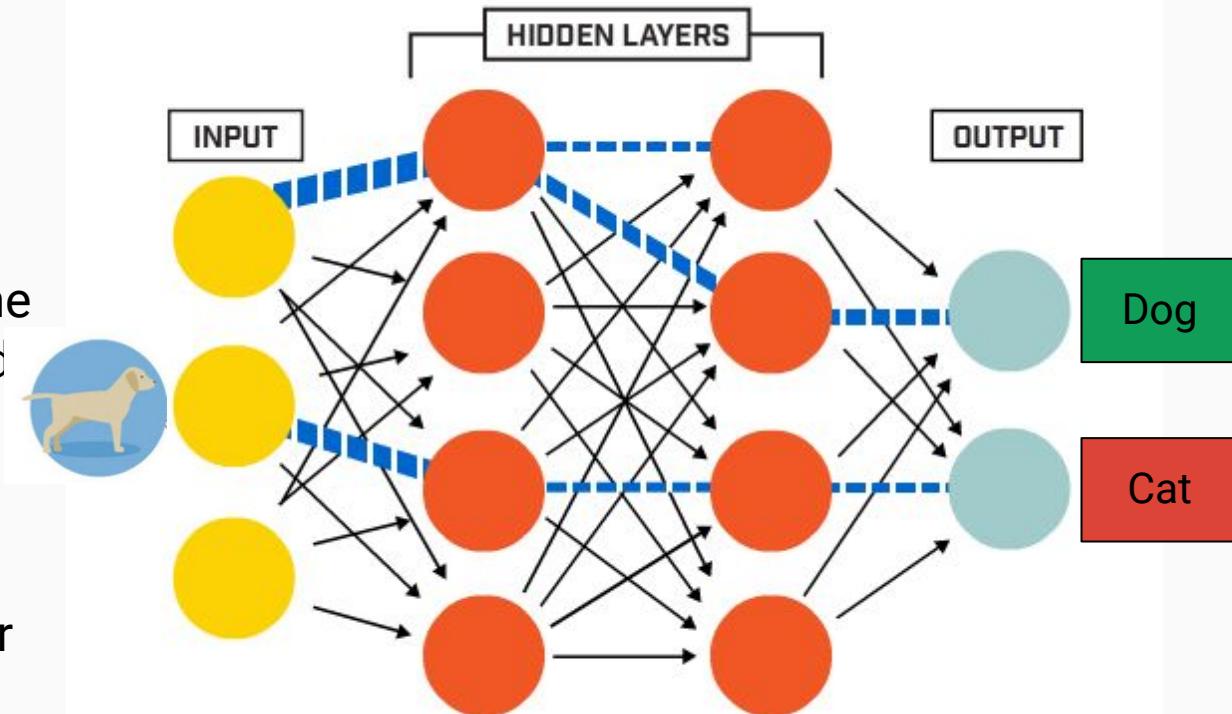


*Animation from youtuber [nang](#)*

# Machine Learning Example: Classification with Neural Net

## Neural Network “activation” functions

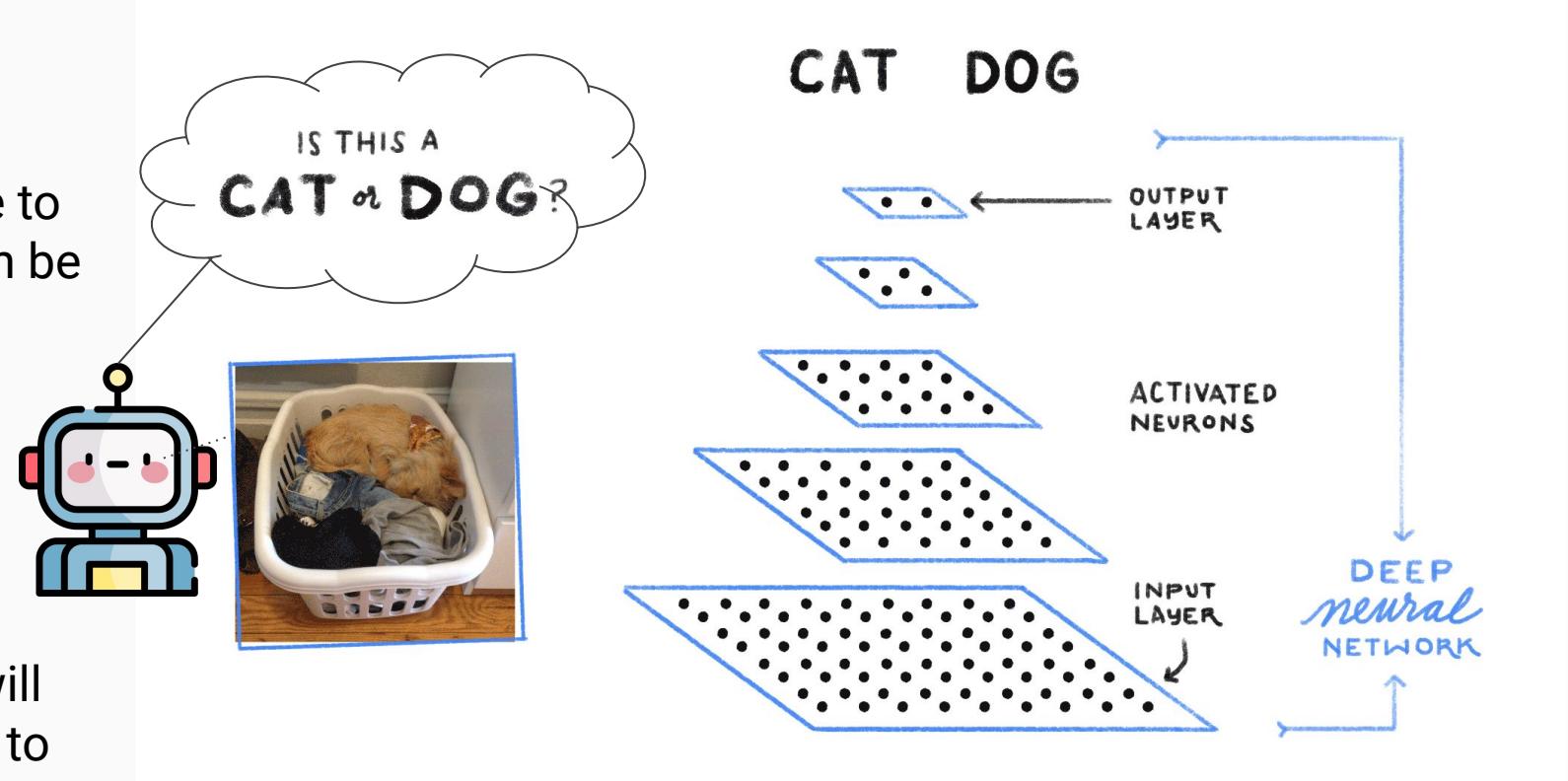
- When a model is trained, the weights & biases are modified to maximize the correctness of the output determined via an **objective function**
- The output of all layers encode the “answer” to a question, such as the classification of an object (yes/no for each output node option)
- Note only outputs in the output layer can be used to answer questions



# Machine Learning Example: Classification with Neural Net

## Neural network behavior

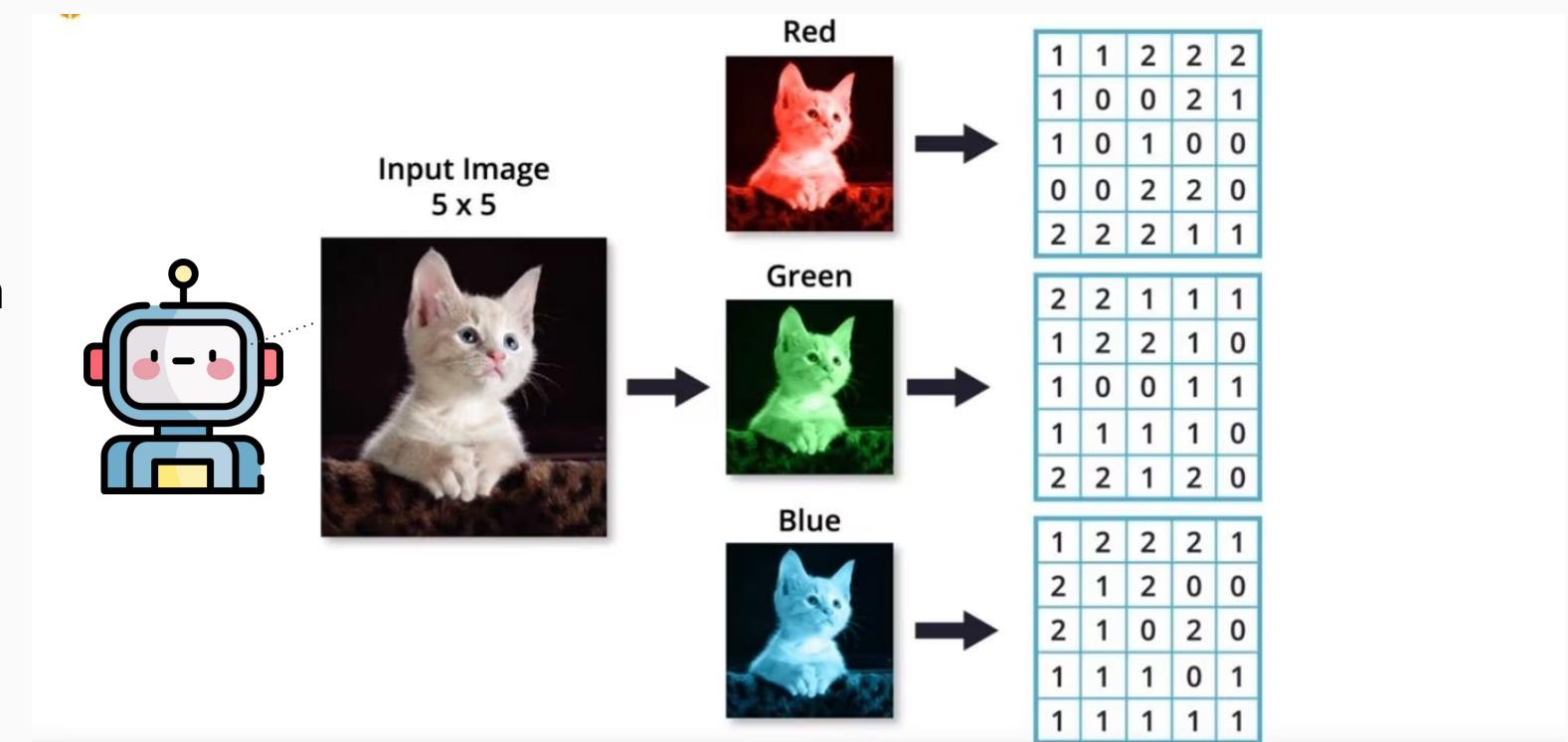
- Visual characteristics we use to differentiate cats vs dogs can be translated into classification properties as part of the activation functions of the neurons
  - Size, Shape, Tail
- Only if features are present will the neurons activate, leading to the desired output (i.e dog)



# Machine Learning Example: Classification with Neural Net

**Recap: Images are made up of pixels, containing (Red, Green, Blue) values**

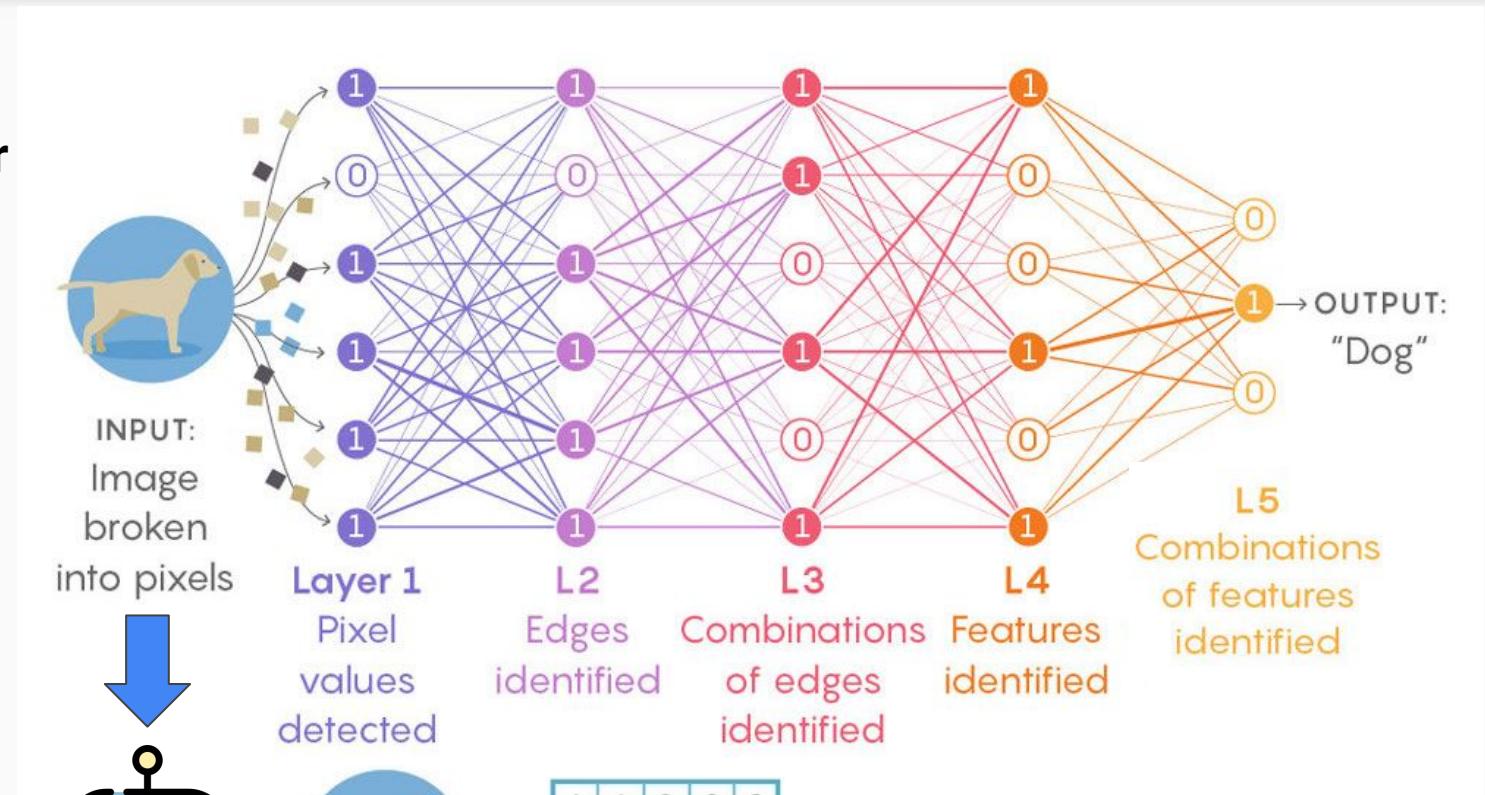
- All colors can be formed from red/green/blue (RGB) values
- Images can be represented numerically in matrixes
- Basis of **computer vision**



# Machine Learning Example: Classification With Neural Net

## Neural network based dog classifier

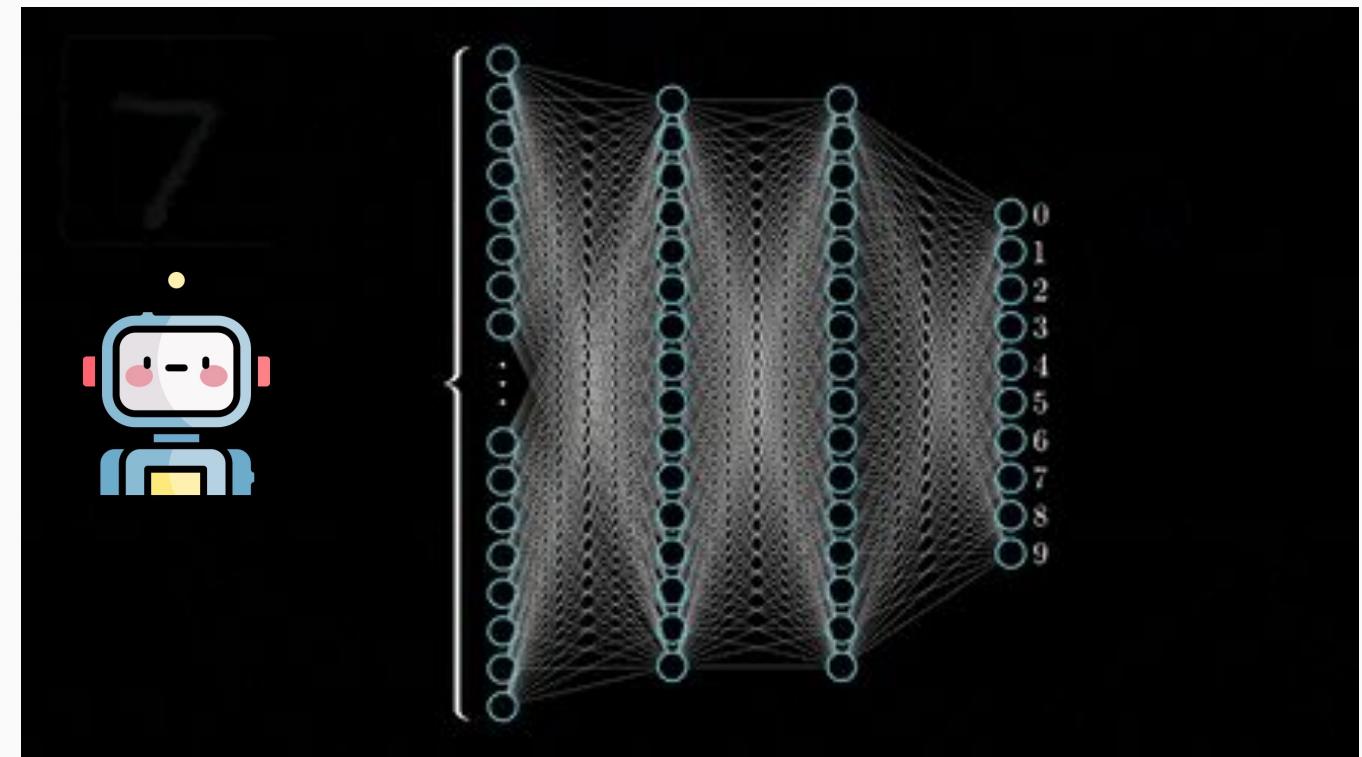
- Images can be represented numerically (pixel values)
- Numbers can be processed mathematically with functions to identify edges in an image
- The combination of edges make up features (i.e legs, tail, snout, ears)
- The combination of features can classify the animal



# Machine Learning Example: Classification With Neural Net

**Same principle can be used to classify / read numbers**

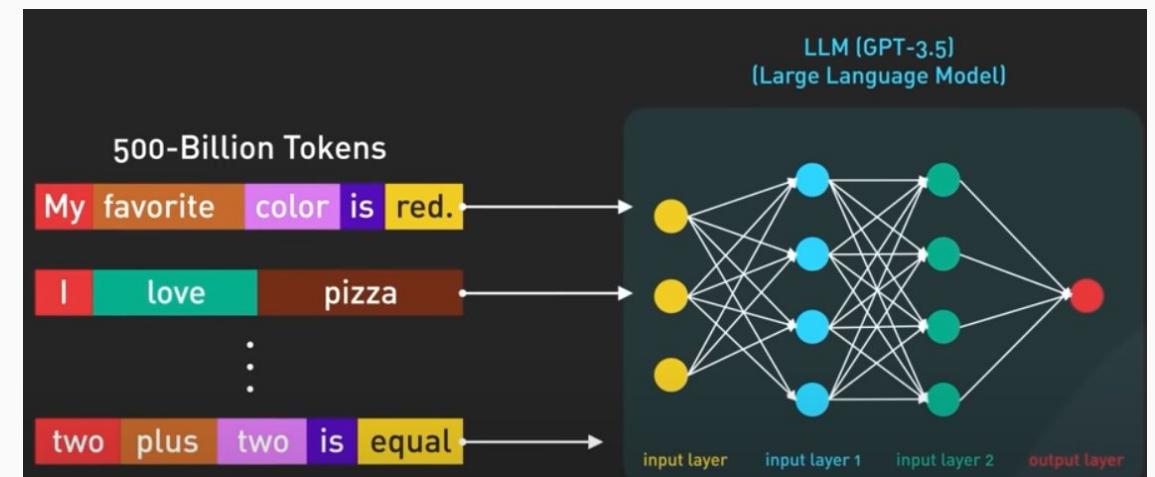
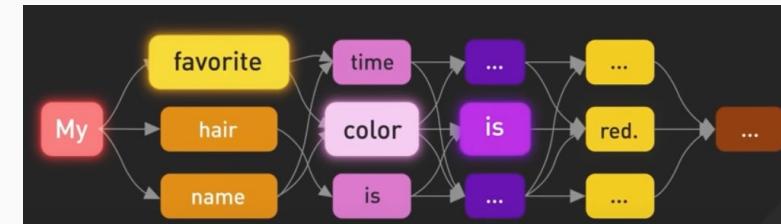
- Image of number represented by pixels
- Pixels fed into different layers which “activate” based on which parts of the image are white
- The hidden layers are setup so that there is a unique property for each number (i.e, how many straight line segments vs curves does the number have)



# Other Examples: How do AI systems generate text?

**Generative AI:** ChatGPT builds on the concepts of neural networks, adding a notion of 'attention' and context to predict the best next word

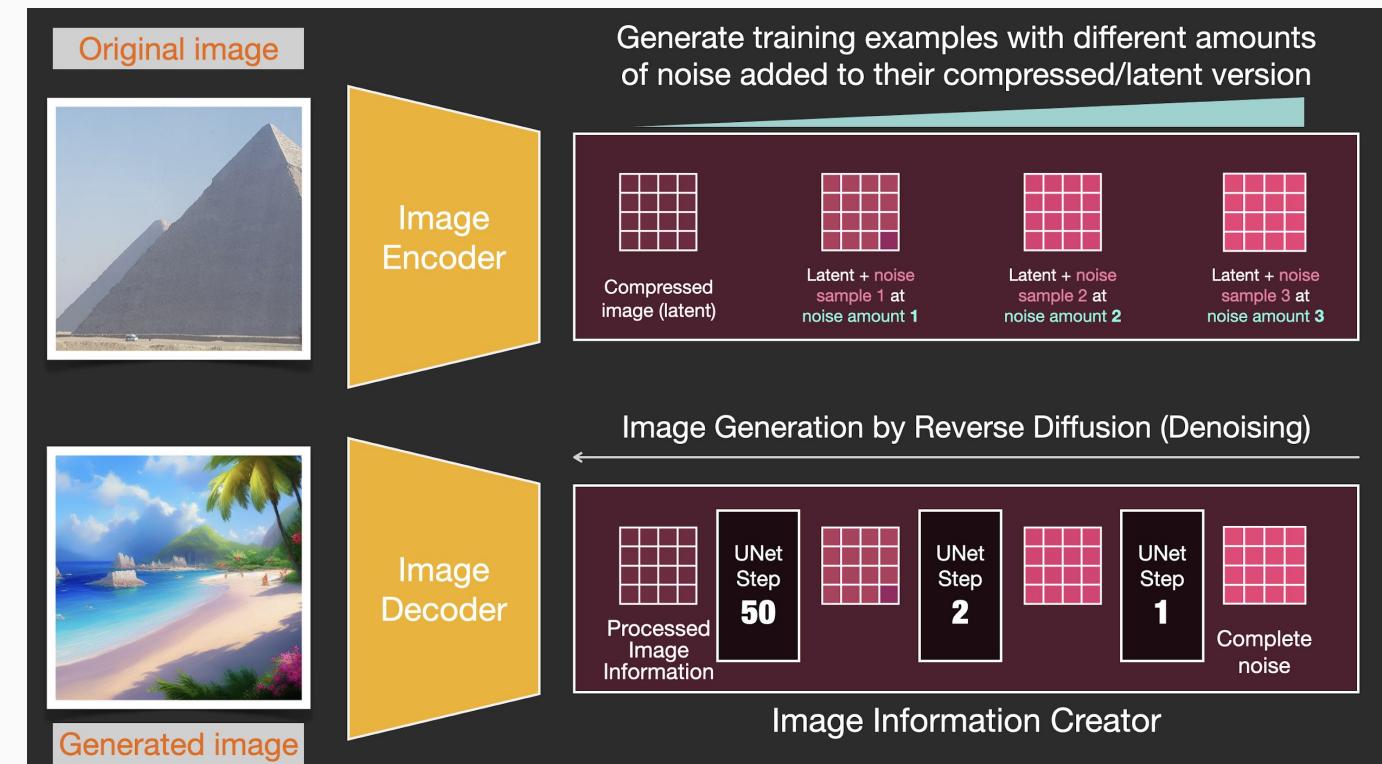
- Training data turns sentences into tokens of words and removes fillers
- The system predicts the next token given the previous tokens/context
- You can think of it as being able to ask someone that's read every useful piece of content online a question
- AgentGPT, AutoGPT, LangChain are other popular gen AI flavors



# Other Examples: How do AI systems generate images?

**Diffusion:** Image generation uses a method referred to as 'diffusion', which uses neural nets to incrementally remove 'noise' from a image to get to a result

- Training data takes images, compresses them, and then adds noise.
- To generate an image, the system starts with a fully noisy environment and incrementally removes the noise attempting to get back to a source image
- Can accept text, or an existing image and additional text as inputs

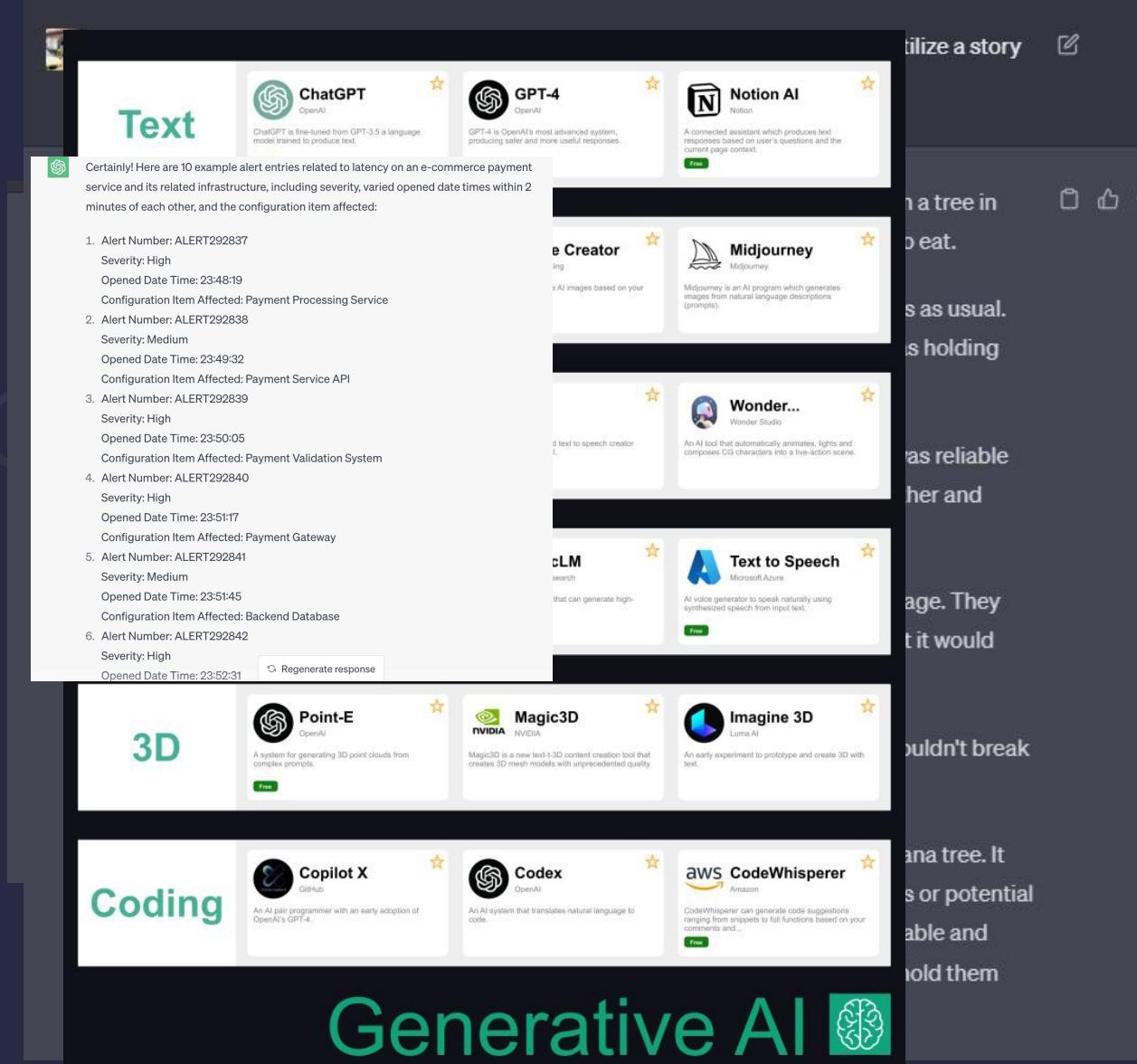


# Bonus: ChatGPT PM Productivity Hacks

As a product manager, you can use prompts for ChatGPT to:

- Write outlines and starting points for epics/prds
  - Turn short descriptions into stories or split existing stories into separate stories
  - Define research questions
  - Identify roadmap opportunities
  - Identify use cases for new technologies like AI/ML within your product/industry
  - Identify design ideas
  - Generate realistic demo data text
  - Identify personas & jobs to be done
  - Industry analysis
  - GTM considerations
- 
- [More prompt ideas](#)
  - [Even more prompt ideas](#)

\*Don't send proprietary data or sensitive



Generative AI

# Your Continued PM AI/ML Learning Journey



What?

## Basic AI ML Concepts

- [\[Coursera\] AI for Everyone](#)
- [DeepLearning.AI Batch AI newsletters](#)
- [Two minute papers youtube channel](#)
- [\[Stanford\] Read the AI Index Report](#)
- Engage in hackathons with your team incorporating cloud or in-house AI
- Familiarize with internal process and approved vendors if needed
- Familiarize with internal capabilities already available to product teams

Why?

## Business Implications for AI ML {pick 1}

- [\[MIT\] Artificial Intelligence: Implications for Business Strategy {6 week, virtual asynch}](#)
- [\[MIT\] AI Strategies and Roadmap: Systems Engineering Approach to AI Development and Deployment {1 week, full day virtual live}](#)

Q3

How?  
*Optional, Technical Depth*

## Continual learning into AI ML technology and algorithms

- [\[Coursera/Stanford\] Machine Learning Specialization {3 week online, virtual asynch}](#)
  - Supervised Machine Learning: Regression and Classification
  - Advanced Learning Algorithms
  - Unsupervised Learning, Recommenders, Reinforcement Learning
- [\[Google\] Generative AI Cloud Skills](#)
- "Designing Machine Learning Systems: An Iterative Process for Production-Ready Applications" by Chip Huyen
- "Building Machine Learning Powered Applications: Going From Idea to Product" by Emmanuel Ameisen

Q4

# AI PM Summary

Learning about AI/ML will help you come up with new **innovative use cases** that can help you provide **greater value & differentiation** to your users, leading to **greater revenue capture**

- Not every problem requires AI to solve
- AI is math, not magic
- Data is key to effective AI