

Harvard

BARNA

Yá'át'ééh 

EASI-22

Edge AI Summer  
Institute 2022

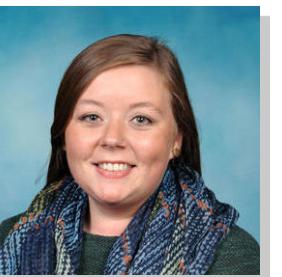
with Navajo Tech

# Hi! I'm Brian!

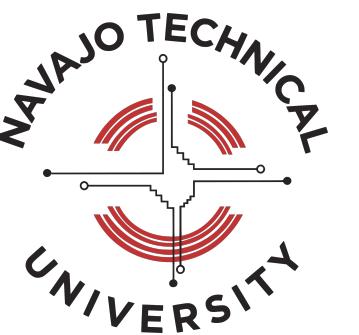
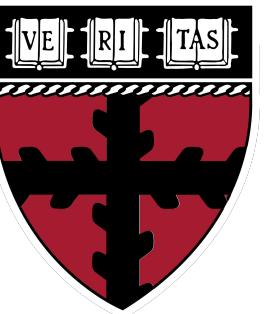
I'm an Assistant Professor of Computer Science  
at **Barnard College, Columbia University**



# Our team!



with help from **many more**



# Our website!

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[tinyMLEdu.org/EASI-22](https://tinyMLEdu.org/EASI-22)

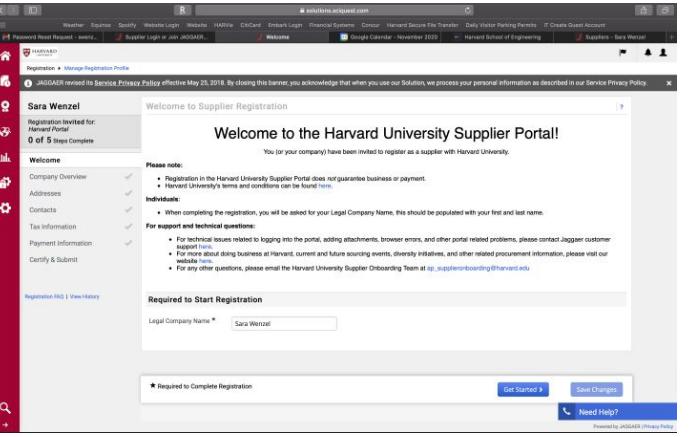
home base for **all information!**

# Make Sure to Pick Up an Arduino Kit!



Question? Contact:  
**Monsuru Ramoni**  
**[mramoni@navajotech.edu](mailto:mramoni@navajotech.edu)**

# Teachers Sign up for Buy2Pay



Question? Contact:  
**Molly Marshall**  
**mmarshall@seas.harvard.edu**

# Workshop Agenda

Day 1

Introduction to AI and (Tiny)ML

Cloud ML

Day 2

Keyword Spotting for the Navajo Language

Mobile ML

Day 3

Bringing AI/ML from the Cloud to the Edge

Embedded ML

# Today's Agenda

- What is Artificial Intelligence?
- Hands-on: AutoDraw
- What is (Deep) Machine Learning?
- Hands-on: ThingTranslator
- What is Responsible TinyML?
- Summary

# Today's Agenda

- What is Artificial Intelligence?
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# Artificial Intelligence (AI) is when a computer can...

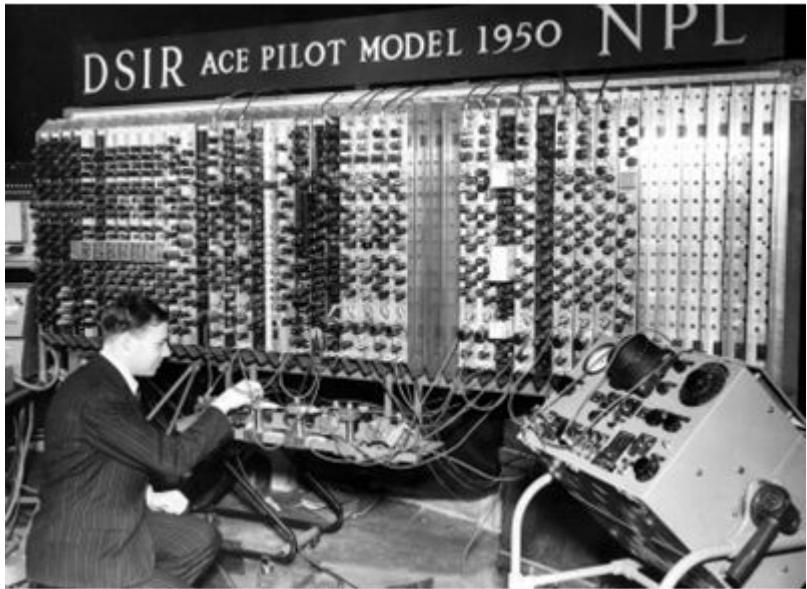
**Think Like A Human**

**Think Rationally**

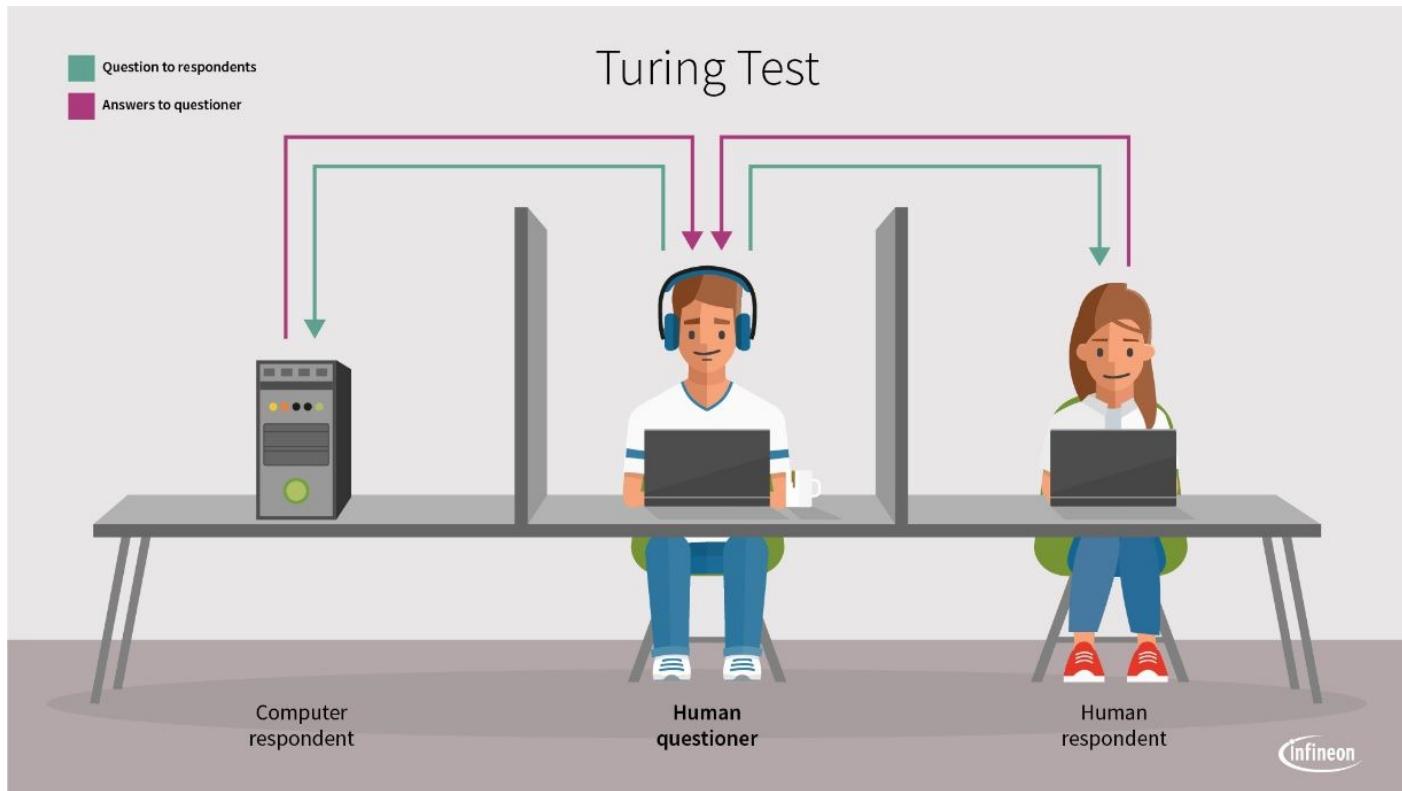
**Act Like a Human**

**Act Rationally**

# The Turing Test



# The Turing Test



# The Turing Test

Chatbots  
can be  
convincing

Q: What is your favorite animal?

A: My favorite animal is a dog.

Q: Why?

A: Because dogs are loyal and friendly.

Q: What are two reasons that a dog might be in a bad mood?

A: Two reasons that a dog might be in a bad mood are if it is hungry or if it is hot.

Q: How many eyes does a giraffe have?

A: A giraffe has two eyes.

Q: How many legs does a frog have?

A: A frog has four legs.

Q: Are there any animals with three legs?

A: No, there are no animals with three legs.

Q: Why don't animals have three legs?

A: Animals don't have three legs because they would fall over.

# The Turing Test

Chatbots  
can be  
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Q: What is your favorite animal?

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A: Because dogs are loyal and friendly.

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A: No, there are no animals with three legs.

Q: Why don't animals have three legs?

A: Animals don't have three legs because they would fall over.

# The Turing Test

But they  
only know  
“what they  
know”

Q: How many eyes does a giraffe have?

A: A giraffe has two eyes.

Q: How many eyes does my foot have?

A: Your foot has two eyes.

Q: How many eyes does a spider have?

A: A spider has eight eyes.

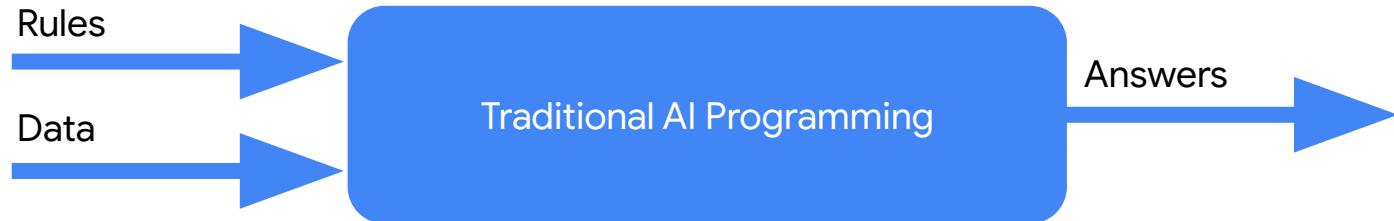
Q: How many eyes does the sun have?

A: The sun has one eye.

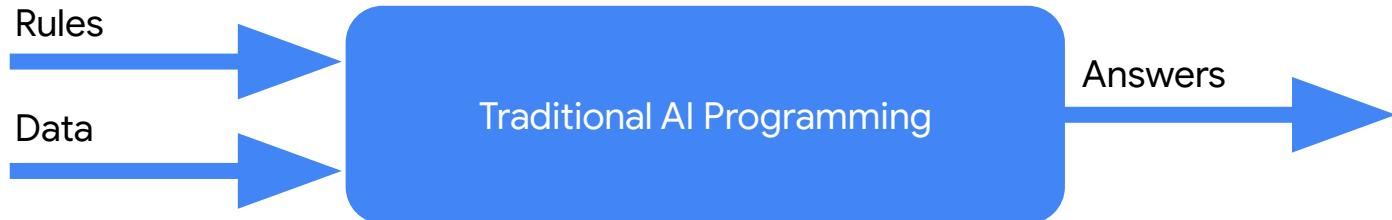
Q: How many eyes does a blade of grass have?

A: A blade of grass has one eye.

# Traditional AI Programming

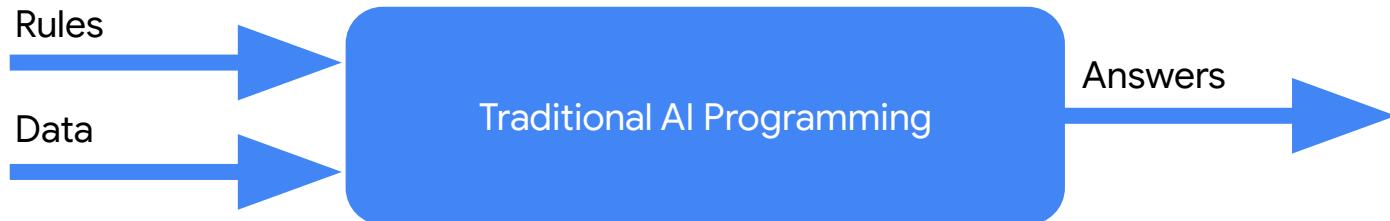


# Traditional AI Programming



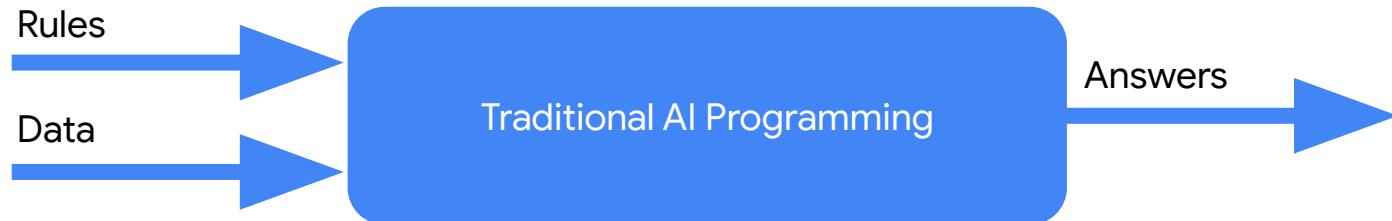
AI is the study of  
**algorithms** that can  
give computers the  
rules they need to be  
**“intelligent”!**

# Traditional AI Programming



```
if(speed<4){  
    status=WALKING;  
}
```

# Traditional AI Programming

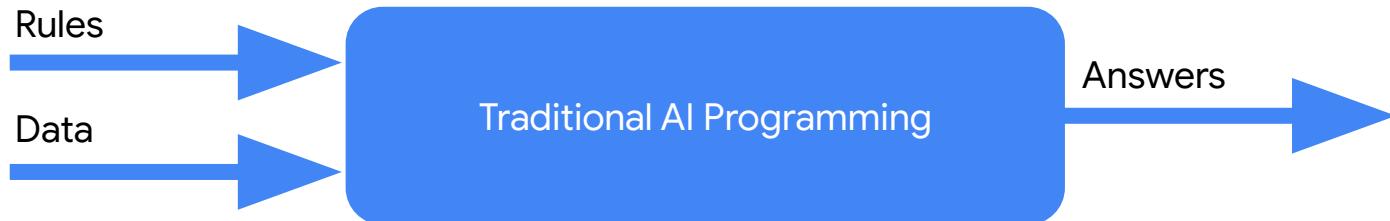


```
if(speed<4){  
    status=WALKING;  
}
```



```
if(speed<4){  
    status=WALKING;  
} else {  
    status=RUNNING;  
}
```

# Traditional AI Programming



```
if(speed<4){  
    status=WALKING;  
}
```



```
if(speed<4){  
    status=WALKING;  
} else {  
    status=RUNNING;  
}
```



```
if(speed<4){  
    status=WALKING;  
} else if(speed<12){  
    status=RUNNING;  
} else {  
    status=BIKING;  
}
```

# Deep Blue



Deep Blue  
IBM chess computer



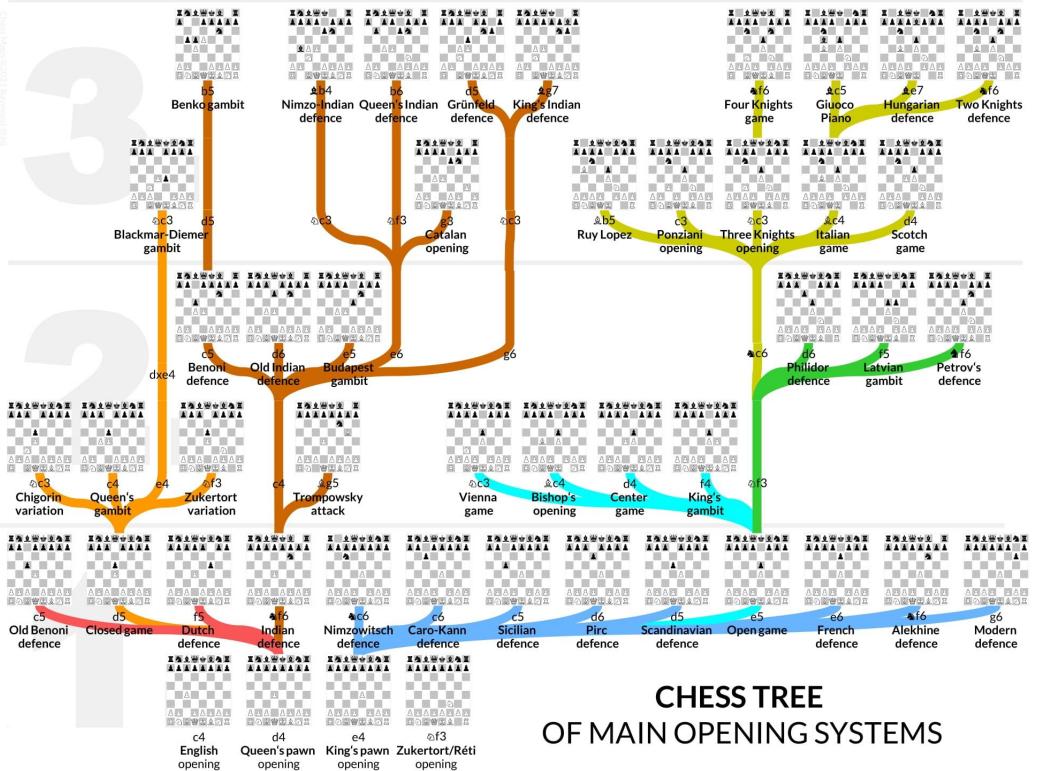
Garry Kasparov  
World Chess Champion

# Deep Blue



On average in any board configuration there are **35** possible moves in chess.

# Deep Blue

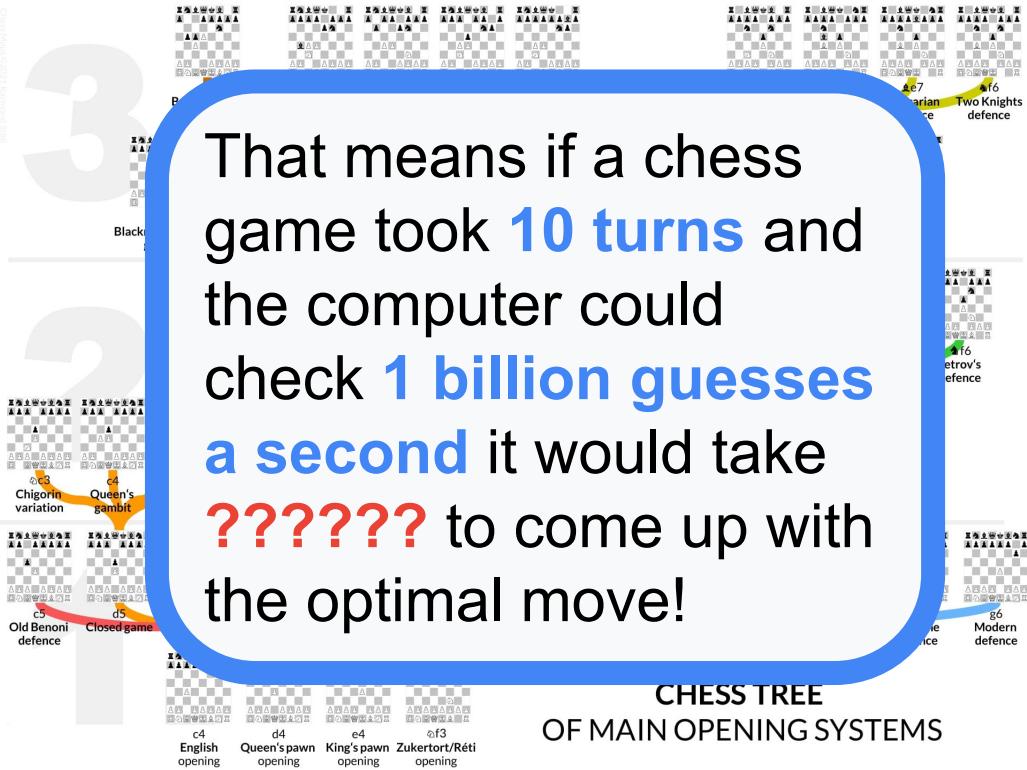


On average in any board configuration there are **35** possible moves in chess.

That means that the computer can search for the move that eventually leads to success with a **35<sup>turns</sup>** guesses

# Deep Blue

That means if a chess game took **10 turns** and the computer could check **1 billion guesses a second** it would take **???????** to come up with the optimal move!

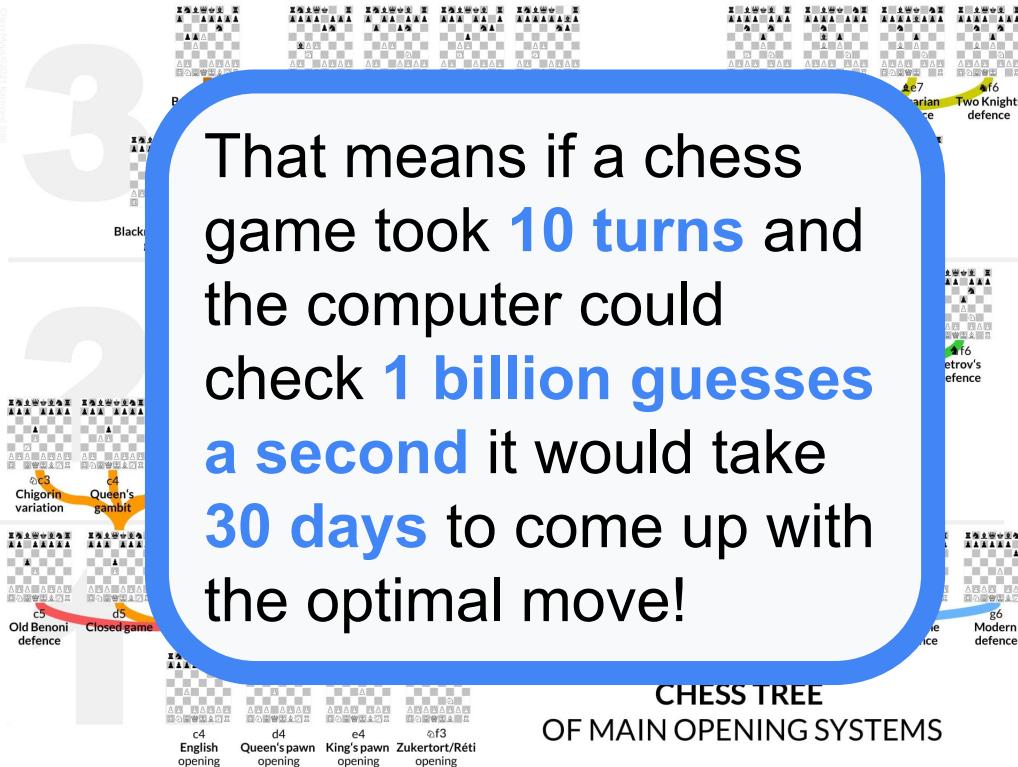


On average in any board configuration there are **35** possible moves in chess.

That means that the computer can search for the move that eventually leads to success with a **35<sup>turns</sup>** guesses

# Deep Blue

That means if a chess game took **10 turns** and the computer could check **1 billion guesses a second** it would take **30 days** to come up with the optimal move!



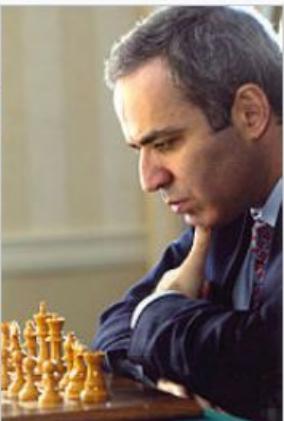
On average in any board configuration there are **35** possible moves in chess.

That means that the computer can search for the move that eventually leads to success with a **35<sup>turns</sup>** guesses

# Deep Blue

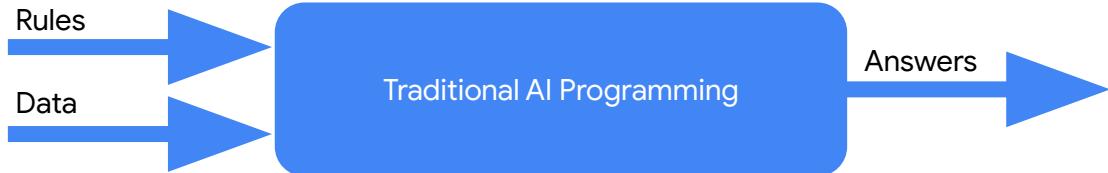


Deep Blue  
IBM chess computer



Garry Kasparov  
World Chess Champion

So deep blue searched  
~7 turns ahead and  
relied on a **board  
scoring rule** created by  
the programmers!



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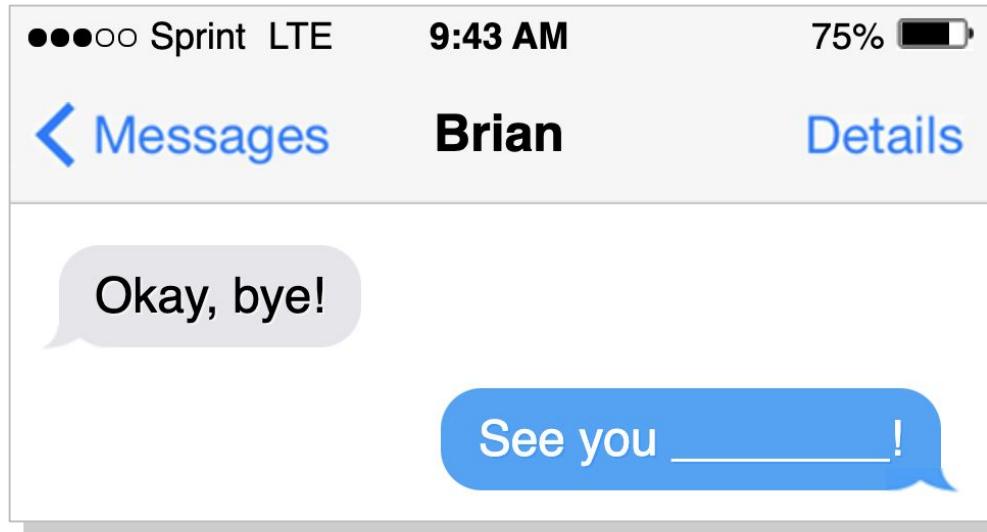
# Today's Agenda

- What is Artificial Intelligence?
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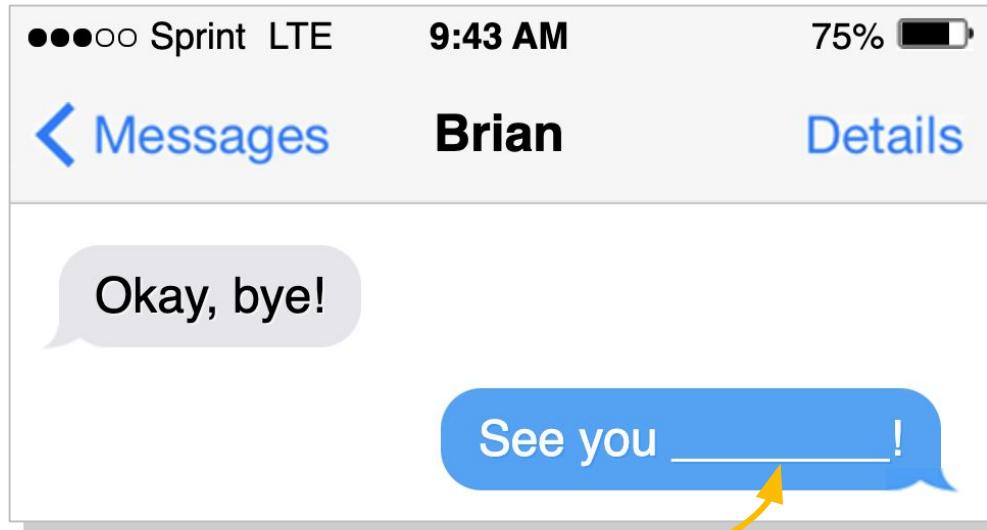
# Experiments with Google

This is an  
**A.I.**  
**Experiment**

# Fill in the blank

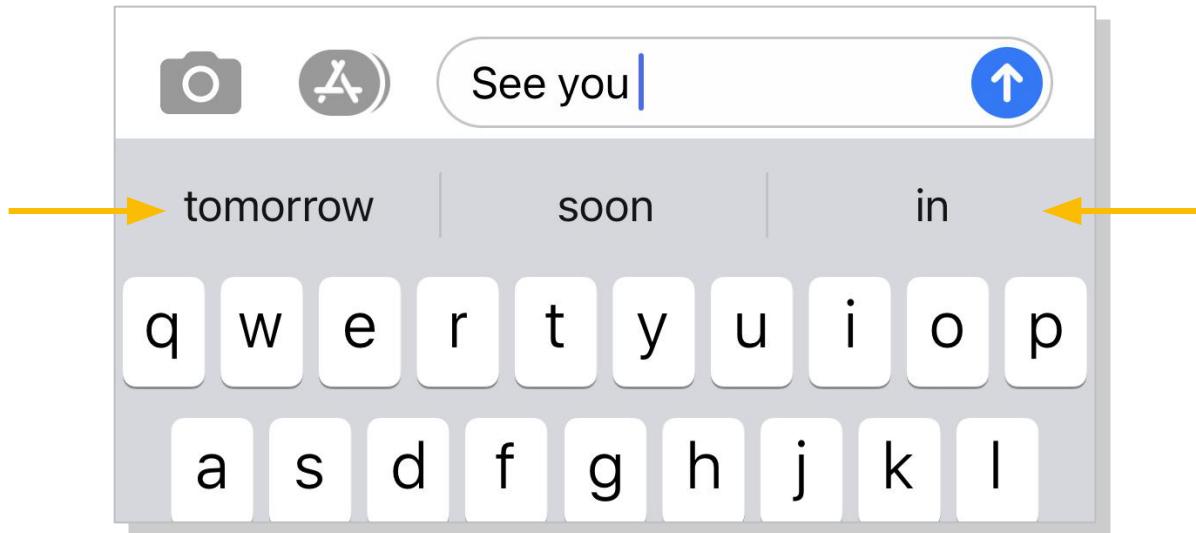


# Fill in the blank

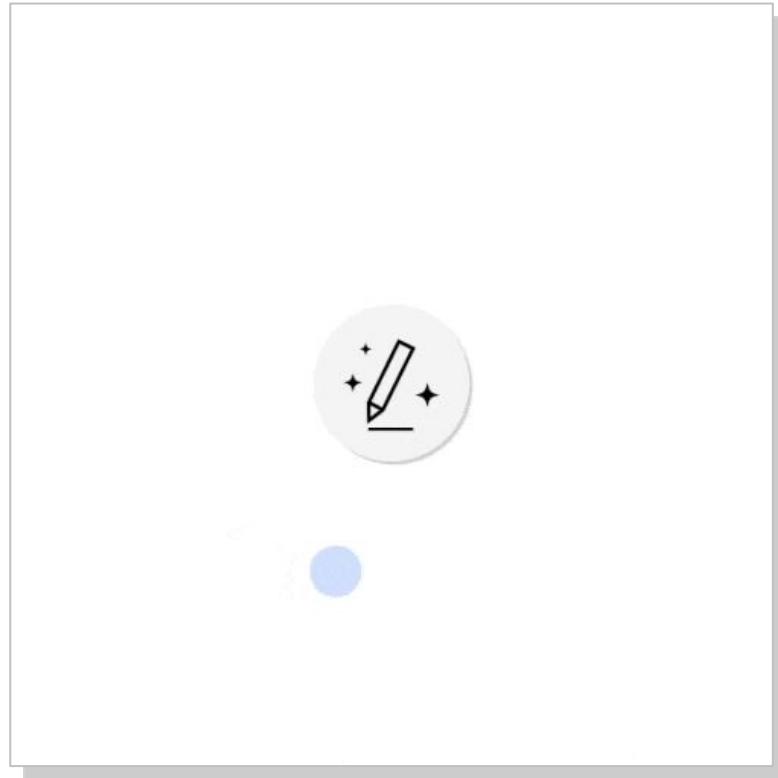


tomorrow  
later

# Prediction: autocomplete



# AutoDraw



# AutoDraw



# Discussion Groups

1. Do you think the AI did a **good job?** 
2. **Why** do you think the AI did  
(or did not) **work well?**
3. **How** do you think the AI is working  
to solve this task? 
4. What types of things were **particularly hard or easy** for the AI?



anything else?

# Today's Agenda

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- **Hands-on: AutoDraw**
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# Today's Agenda

- What is Artificial Intelligence?
- Hands-on: AutoDraw
- **What is (Deep) Machine Learning?**
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# Artificial Intelligence

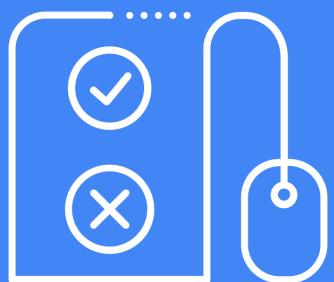
# Machine Learning

*What's the  
difference?*

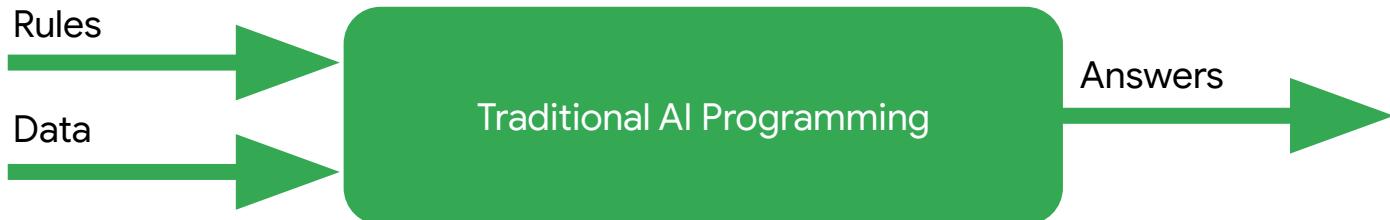


# Artificial Intelligence

## Machine Learning



# Traditional AI Programming



```
if(speed<4){  
    status=WALKING;  
}
```

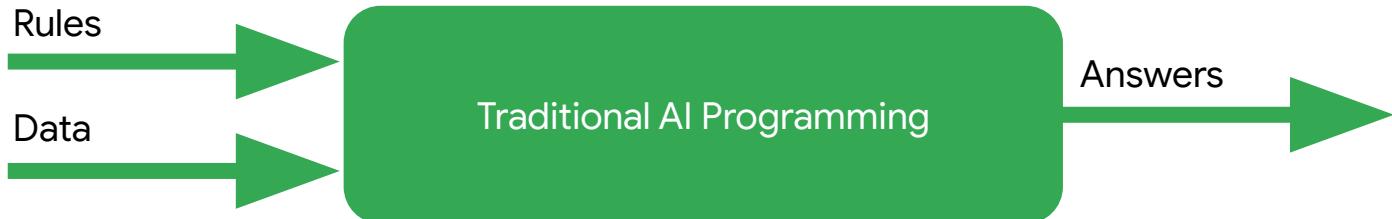


```
if(speed<4){  
    status=WALKING;  
} else {  
    status=RUNNING;  
}
```



```
if(speed<4){  
    status=WALKING;  
} else if(speed<12){  
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# Traditional AI Programming



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```
if(speed<4){  
    status=WALKING;  
} else if(speed<12){  
    status=RUNNING;  
} else {  
    status=BIKING;  
}
```



// ???

# Categorize

1



2



3



5



6



4



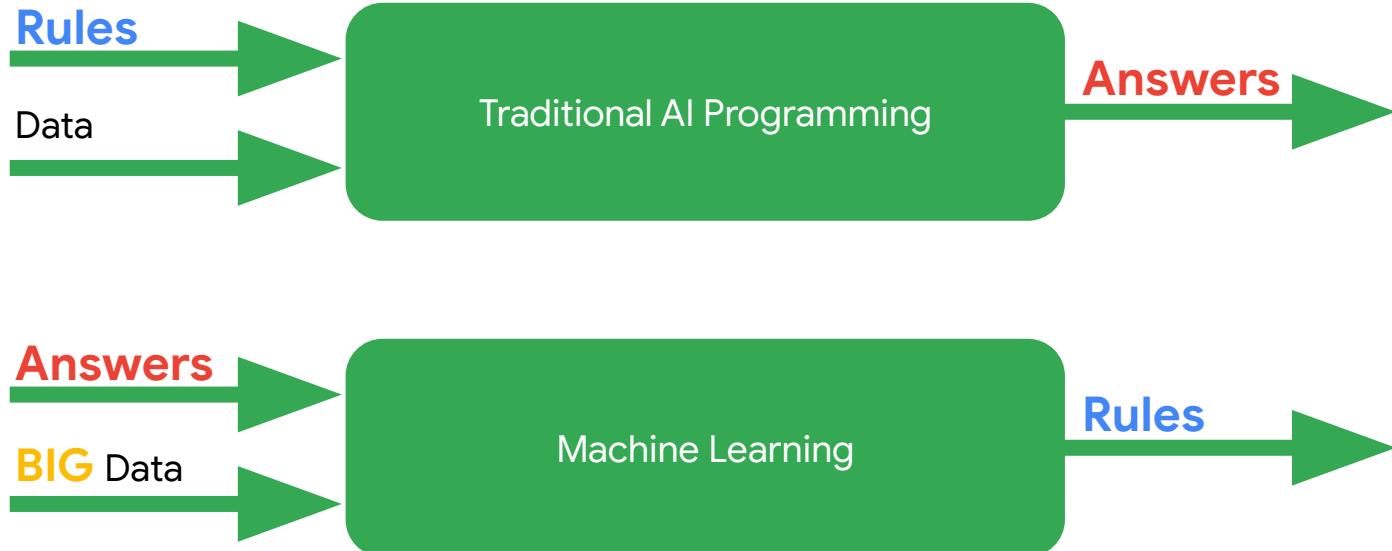
7



8



# The Machine Learning Paradigm



# Activity Detection with Machine Learning



0101001010100101010  
1001010101001011101  
0100101010010101001  
0101001010100101010

1010100101001010101  
0101010010010010001  
001001111010101111  
1010100100111101011

1001010011111010101  
1101010111010101110  
1010101111010101011  
1111110001111010101

1111111111010011101  
0011111010111110101  
0101110101010101110  
1010101010100111110

Label = WALKING

Label = RUNNING

Label = BIKING

Label = GOLFING

# Activity Detection with Machine Learning



0101001010100101010  
1001010101001011101  
0100101010010101001  
0101001010100101010

1010100101001010101  
0101010010010010001  
001001111010101111  
1010100100111101011

1001010011111010101  
1101010111010101110  
1010101111010101011  
1111110001111010101

1111111111010011101  
0011111010111110101  
0101110101010101110  
1010101010100111110

Label = WALKING

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Label = BIKING

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# Activity Detection with Machine Learning



0101001010100101010  
1001010101001011101  
01001010100101011001  
010100101010010101010

1010100101001010101  
0101010010010010001  
0010011110101011111  
10101001001111010111

1001010011111010101  
1101010111010101110  
10101011110101010111  
1111110001111010101

1111111111010011101  
0011111010111110101  
0101110101010101110  
1010101010100111110

Label = WALKING

Label = RUNNING

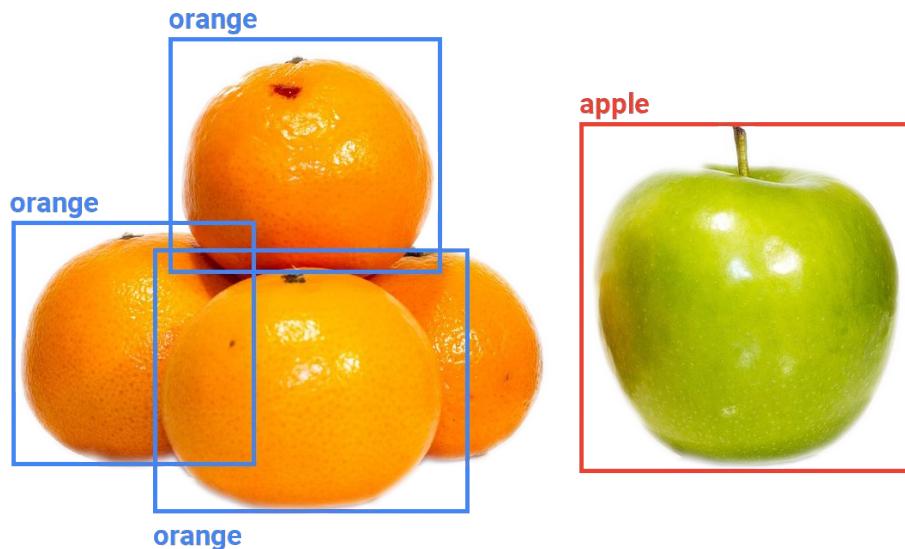
Label = BIKING

Label = GOLFING

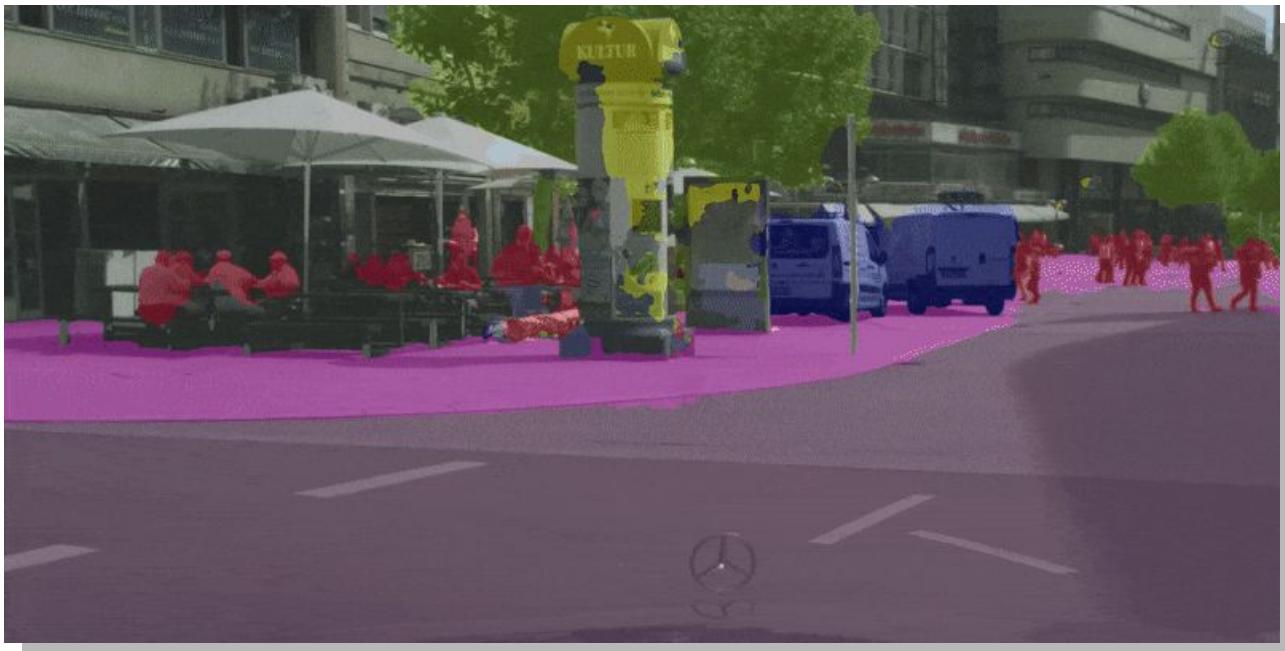
# Review what we've learned

Machine learning provides a computer with data, **rather than explicit instructions**. Using these data, the computer learns to **recognize patterns** and becomes able to execute tasks on its own.

# Object Detection



# Segmentation



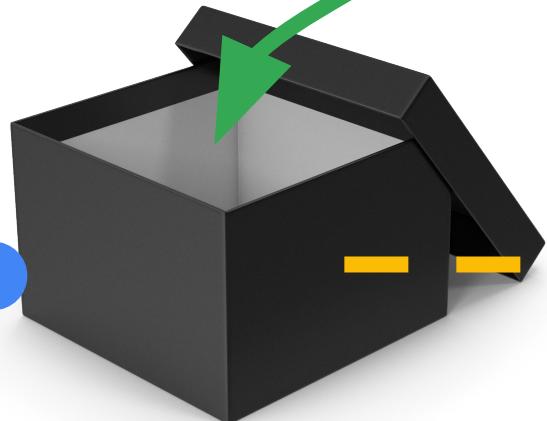
# Training the machine



WE PROVIDE

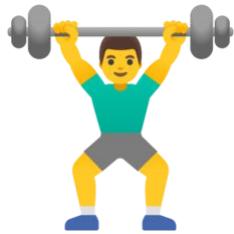
ANSWERS

INPUTS



RULES

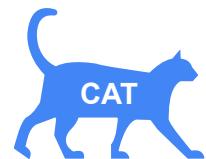
# Training the machine



For a set of  
Input Data

Input, Label

---



# Training the machine



For a set of  
Input Data

Guess the  
Answer  
and count mistakes

Input, Label

Result



Dog ✓



Dog ✗



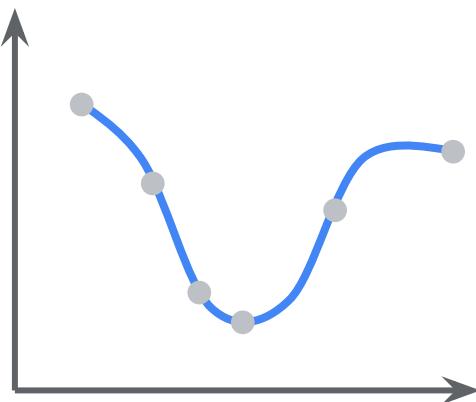
Cat ✓

# Training the machine



Guess the  
Answer  
and count mistakes

Loss  
function of mistakes



# Training the machine



For a set of  
Input Data

Guess the  
Answer  
and count mistakes

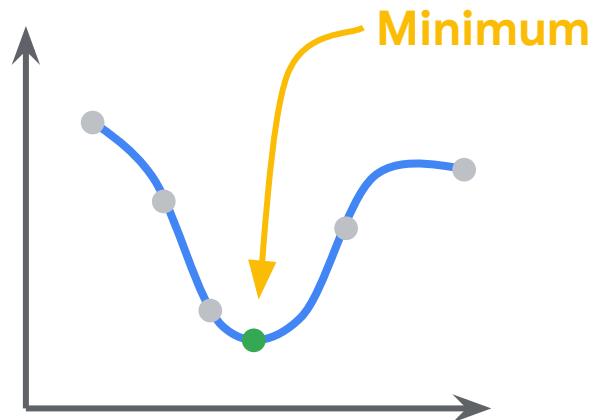
Improve the  
model to be  
more correct

# Training the machine

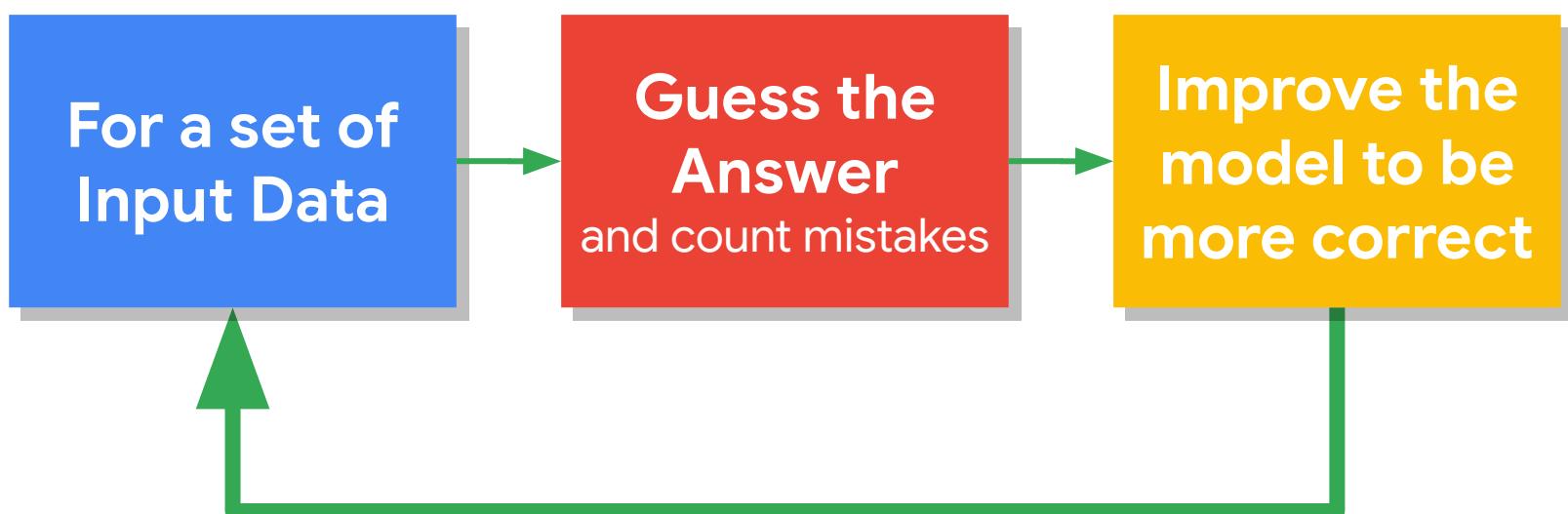


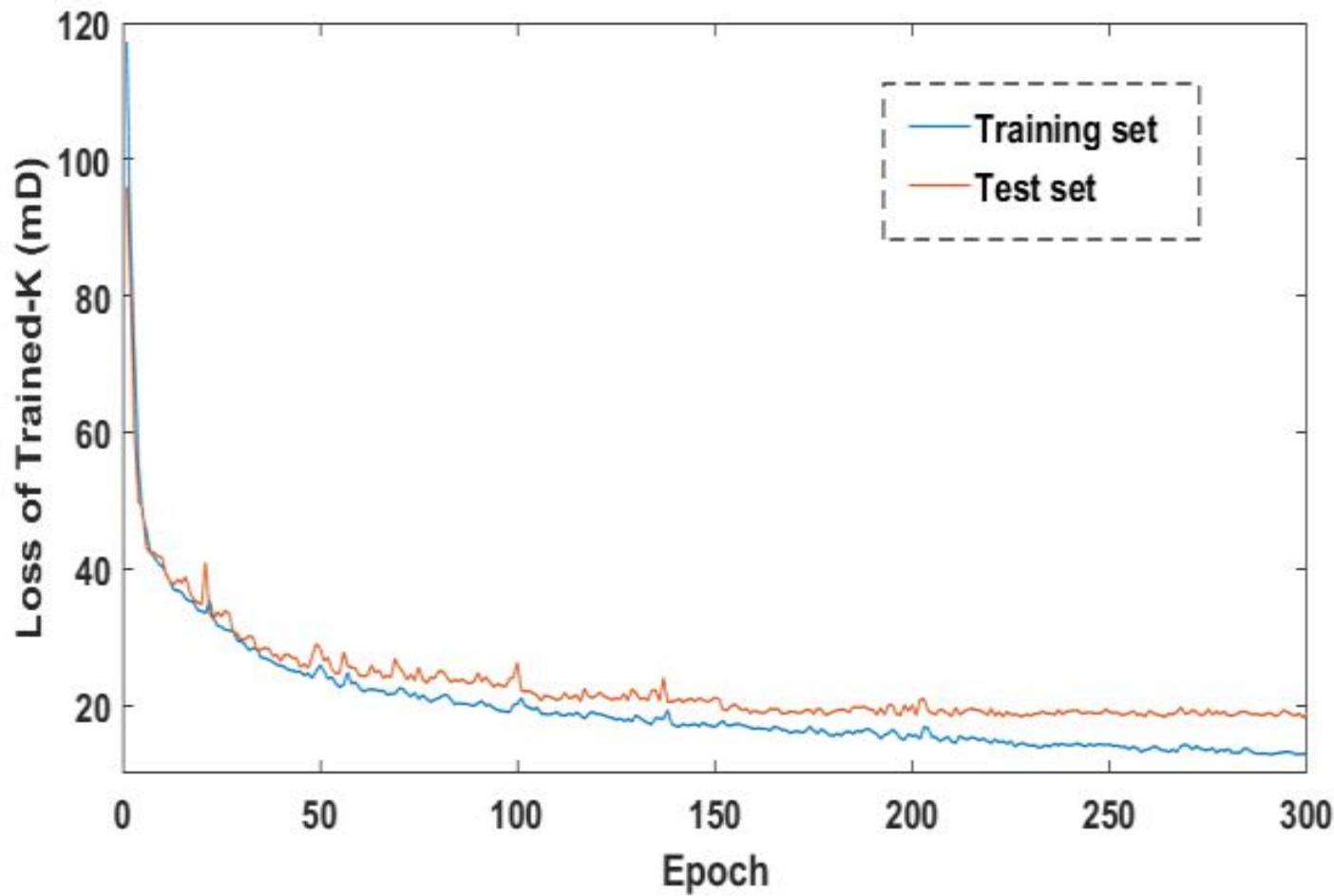
Improve the model to be more correct

Loss  
number of mistakes

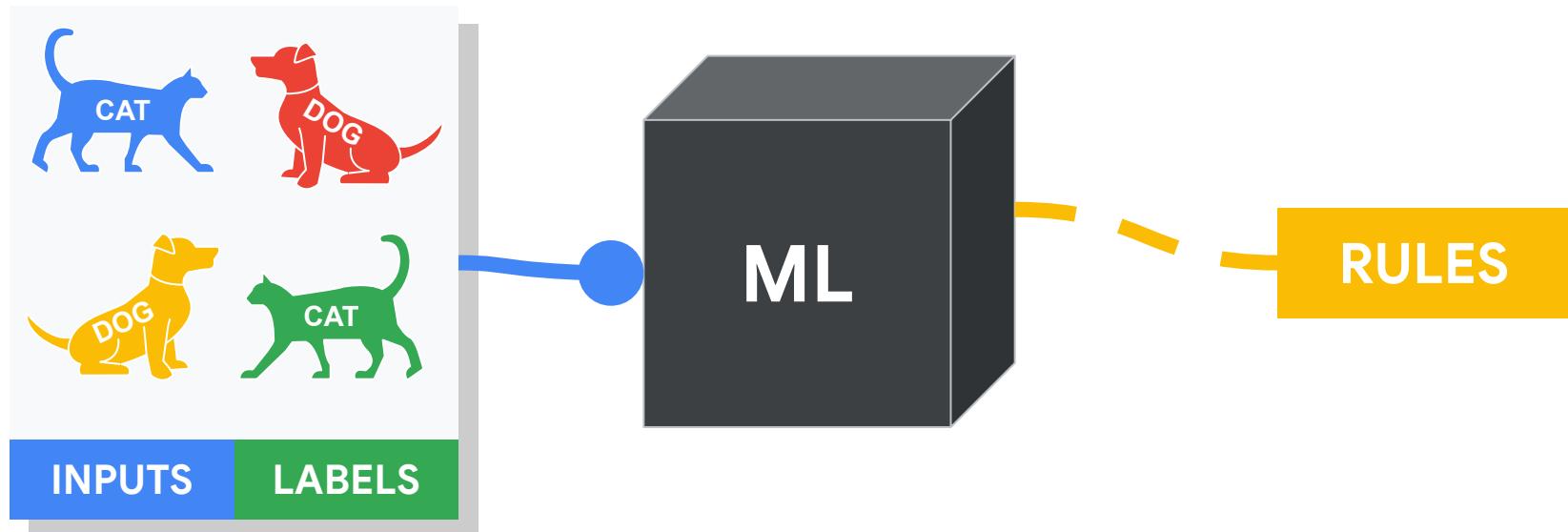


# Training the machine

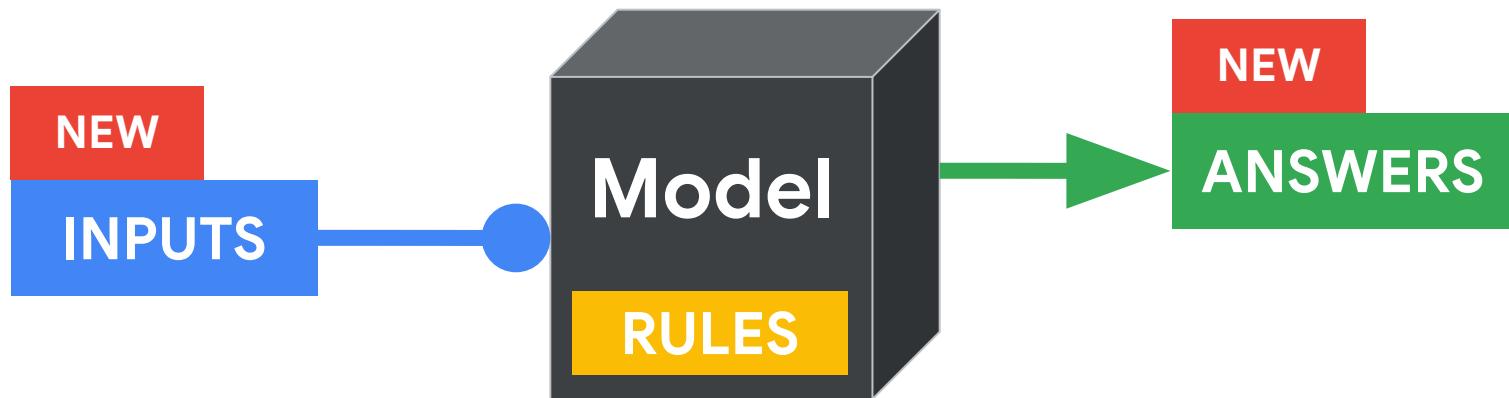




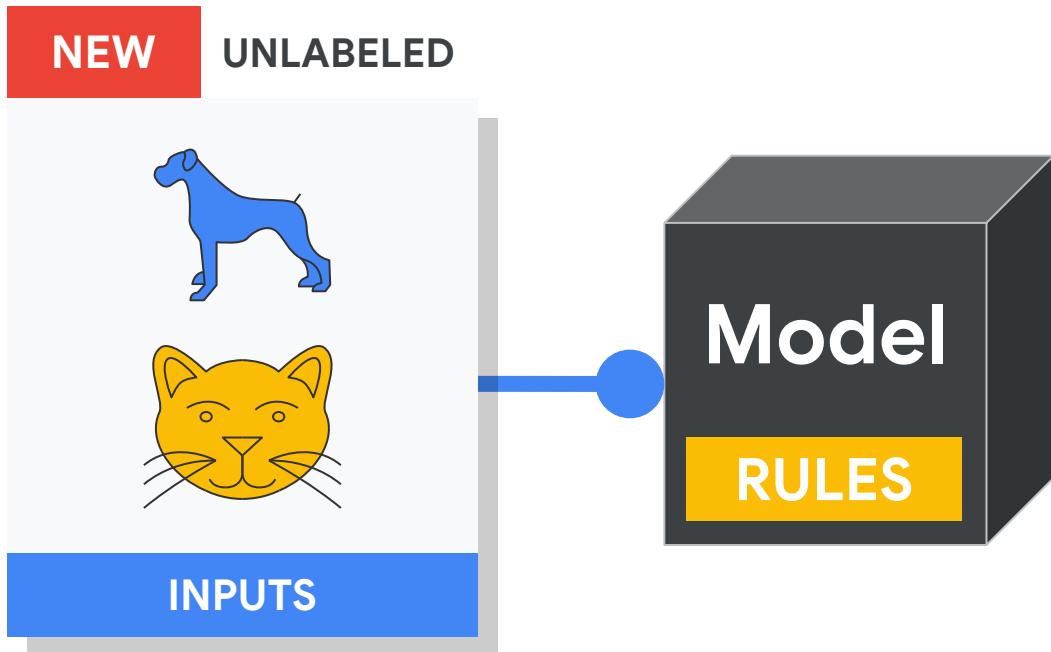
# Training the machine



# After it's learned:

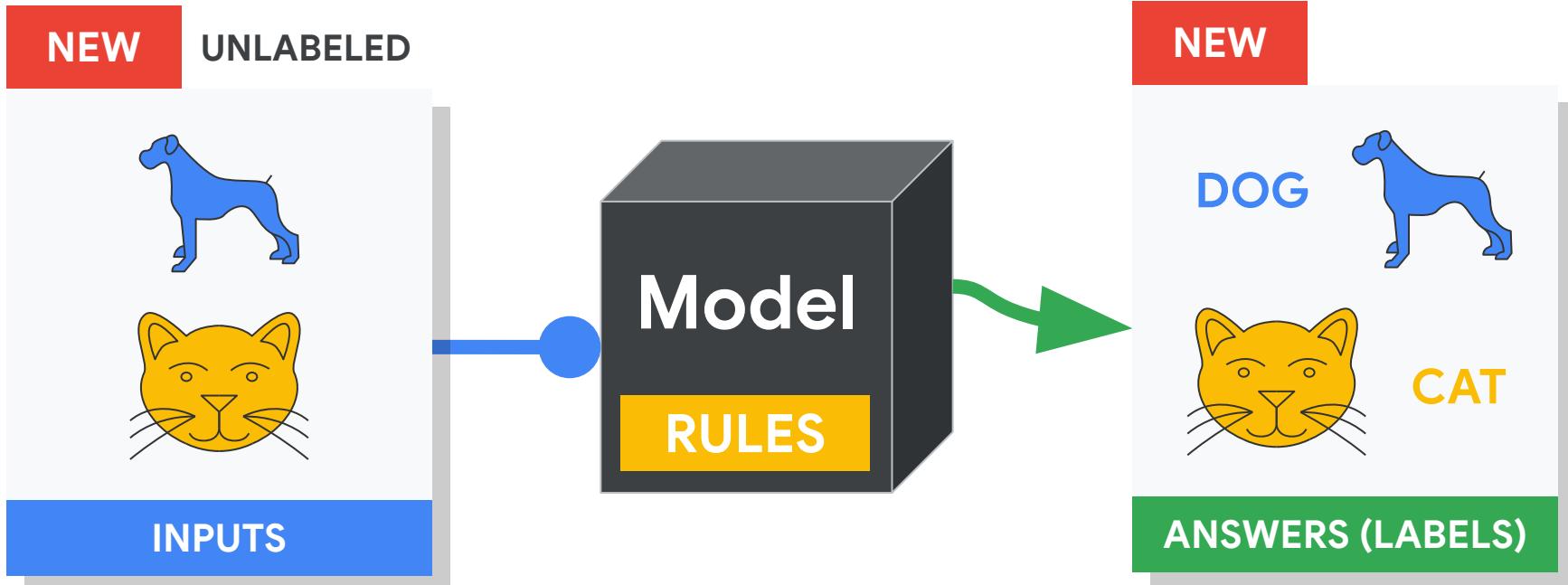


# After it's learned:



# Making predictions:

This is often called  
**INFERENCE!**



Deep  
Learning

Machine  
Learning

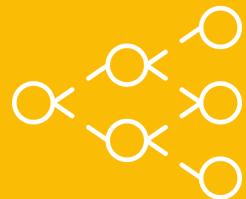
*Ok so what about  
Deep Learning?*



# Artificial Intelligence

## Machine Learning

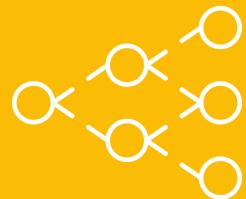
### Deep Learning



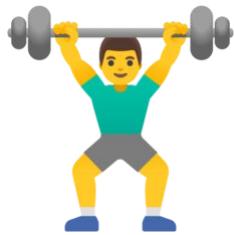
# Artificial Intelligence

## Machine Learning

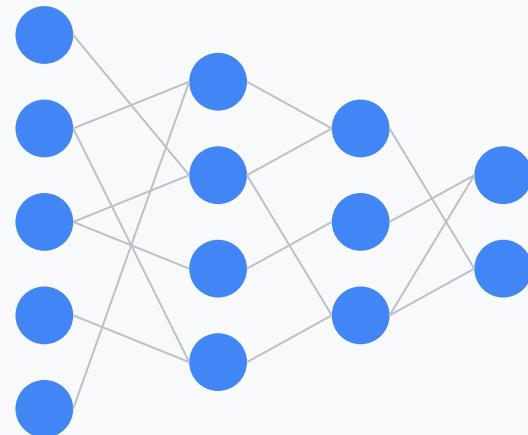
### Deep Learning



# Training the machine

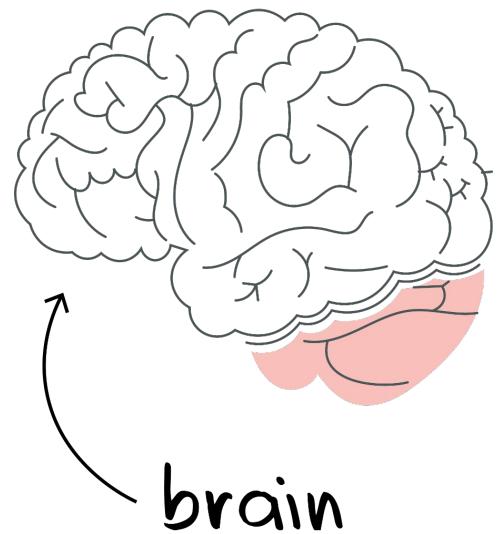


Make a  
Guess!

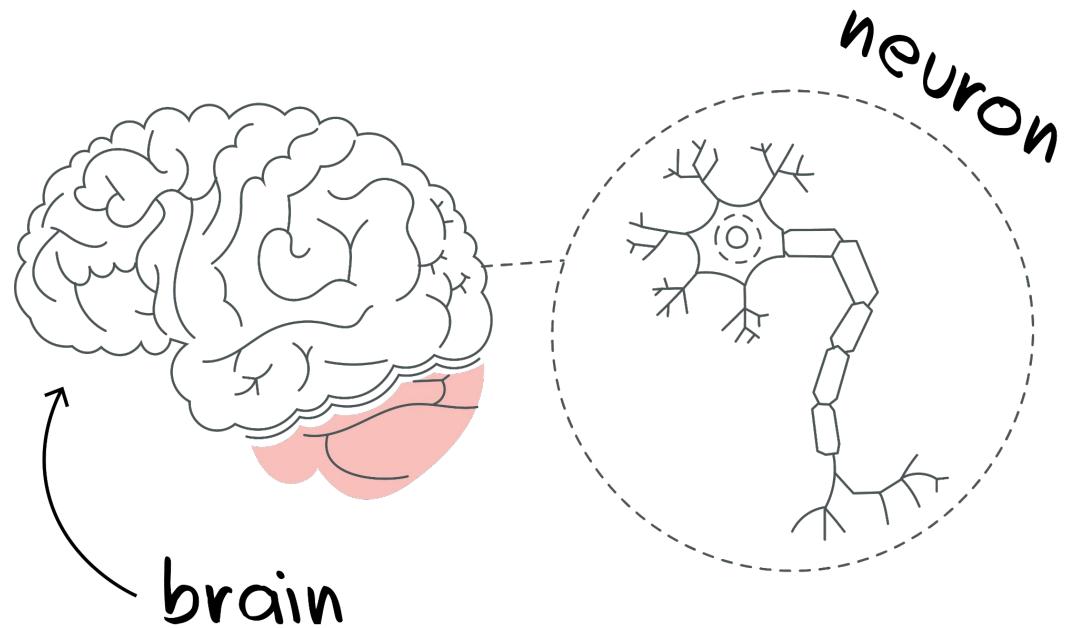


*Neural Network*

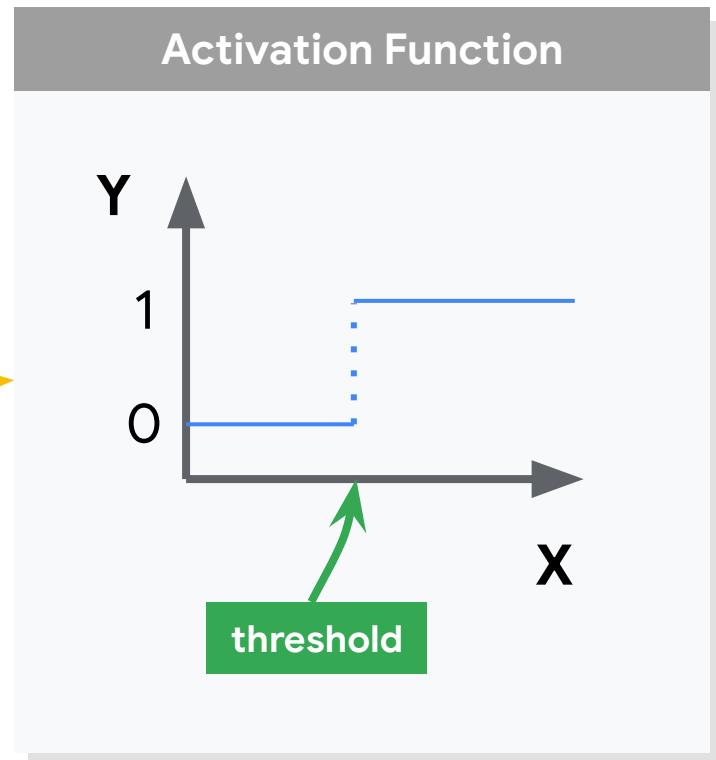
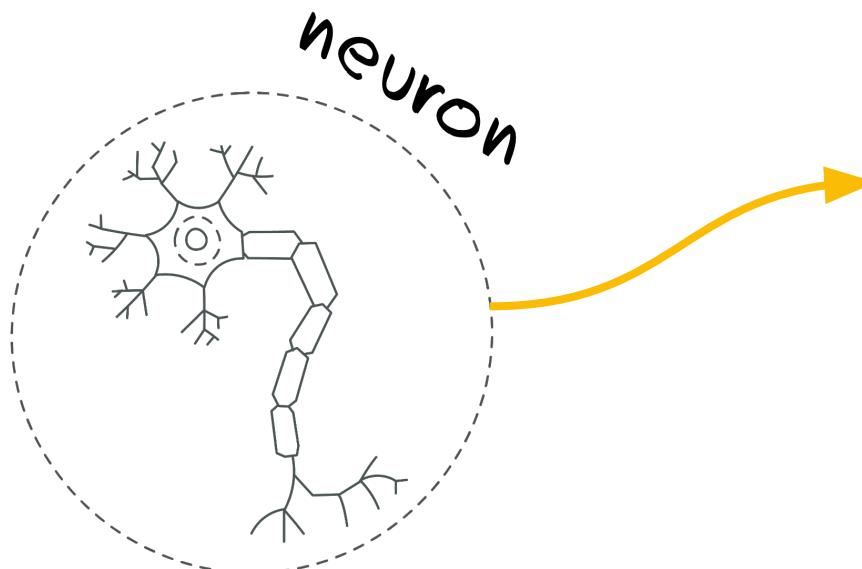
# Neural network



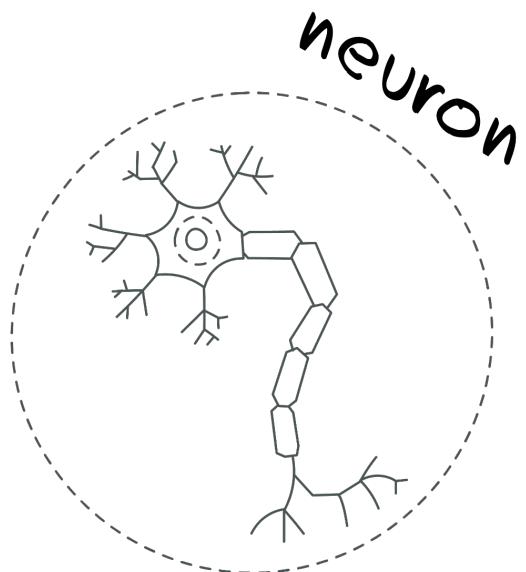
# Neural network



# Neural network



# Neural network

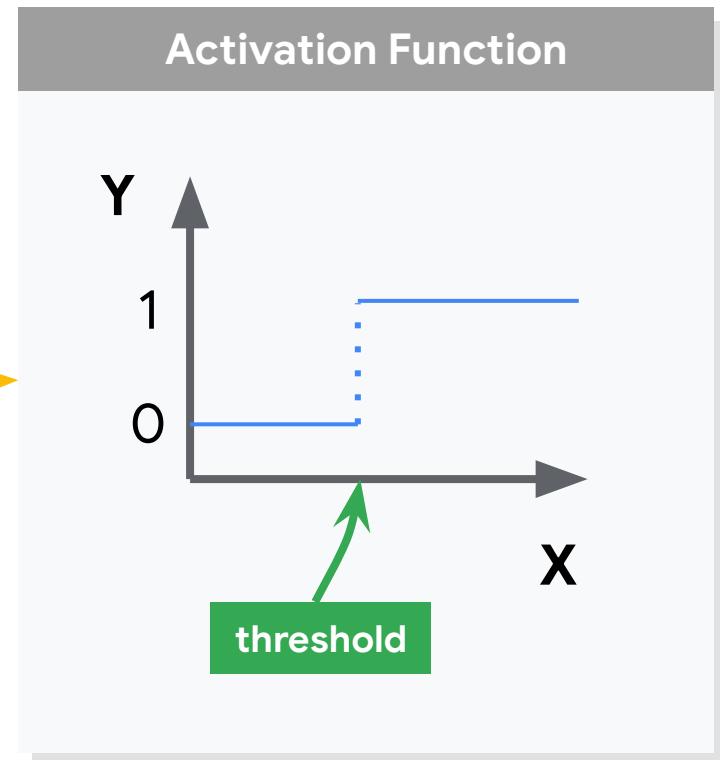
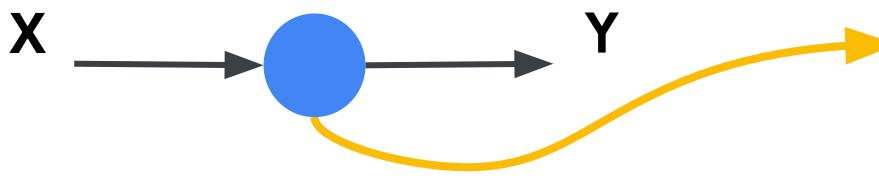


*artificial*

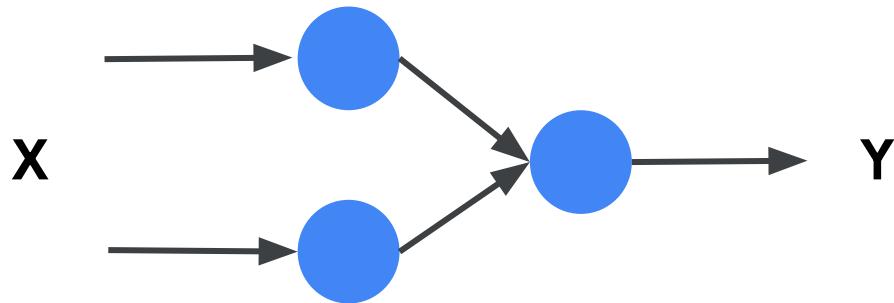
# Neural network



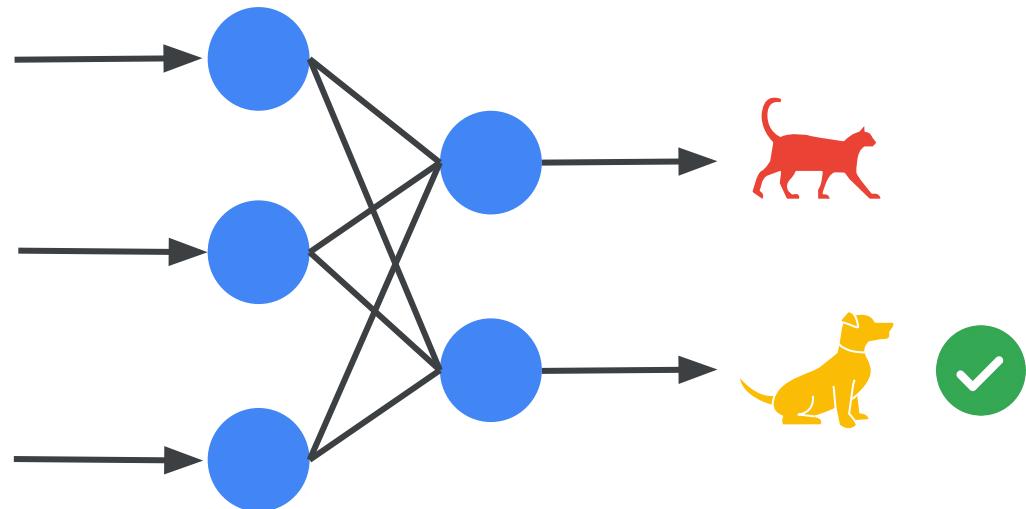
# Neural network



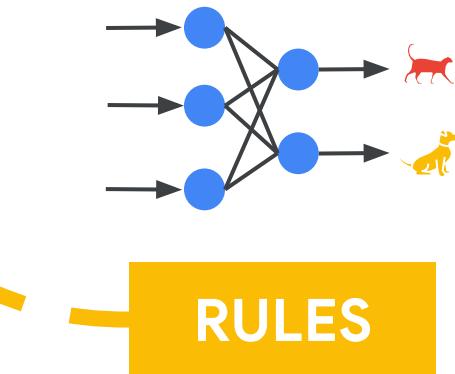
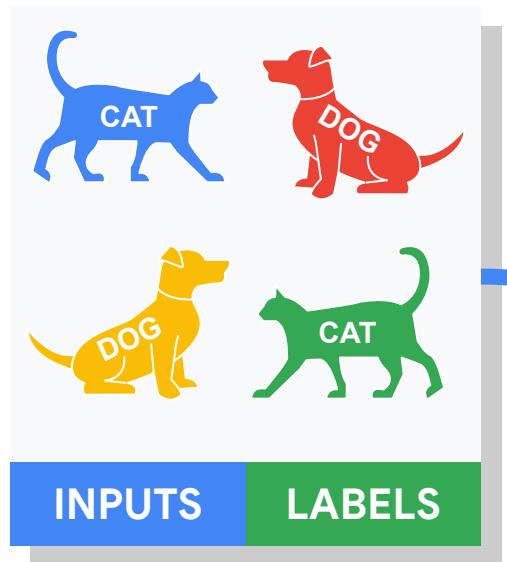
# Multi-layer neural network



# Deep Learning with Neural Networks



# Training the machine



# Case Study: Handwriting

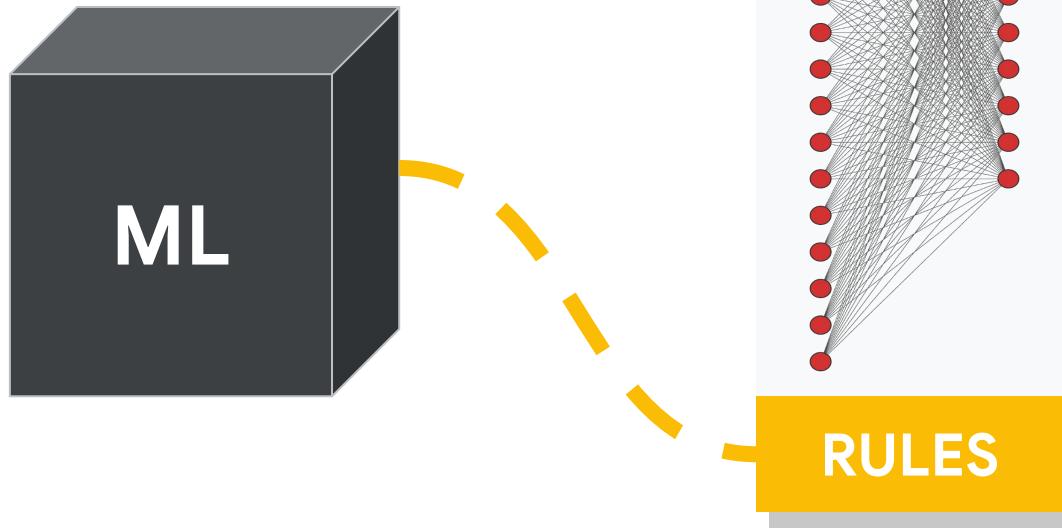
practice  
**DATA**

INPUTS	LABELS
	

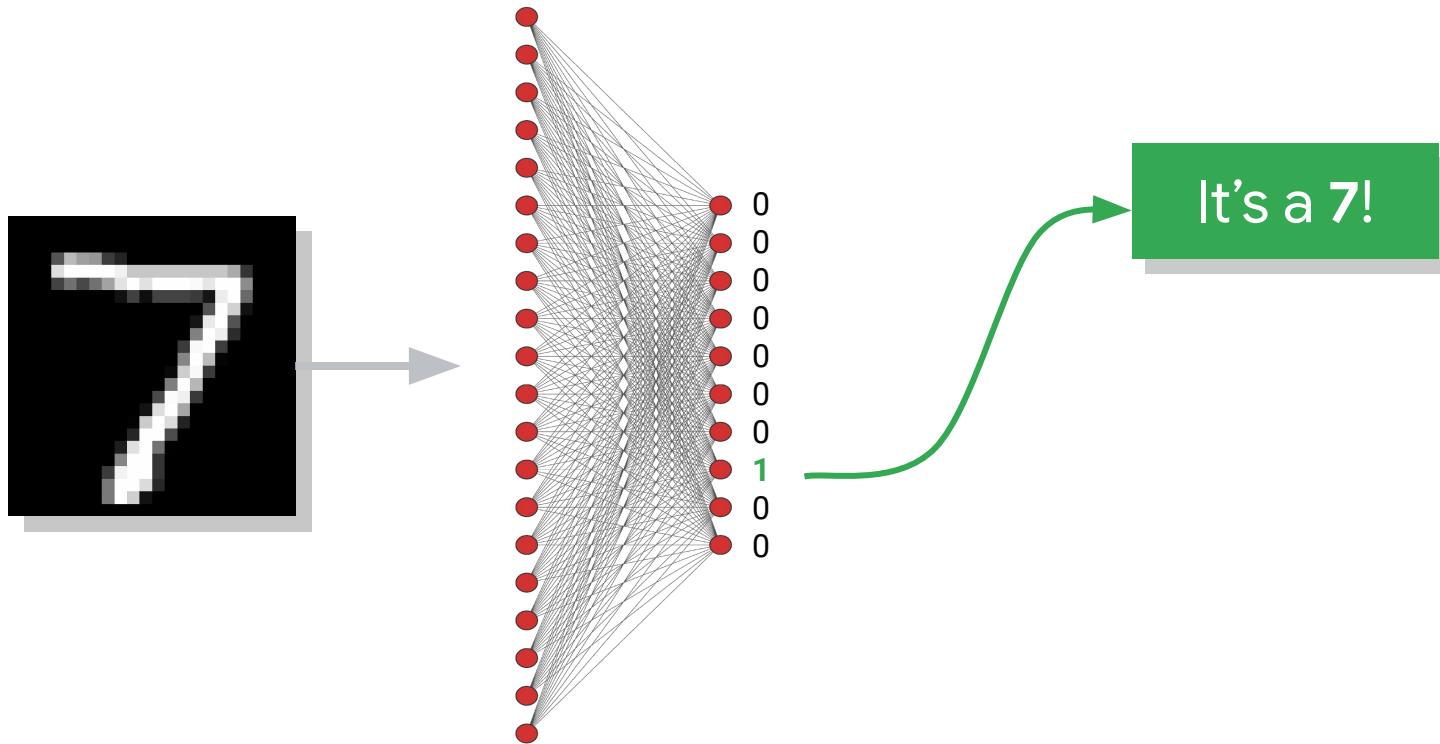
# Case Study: Handwriting



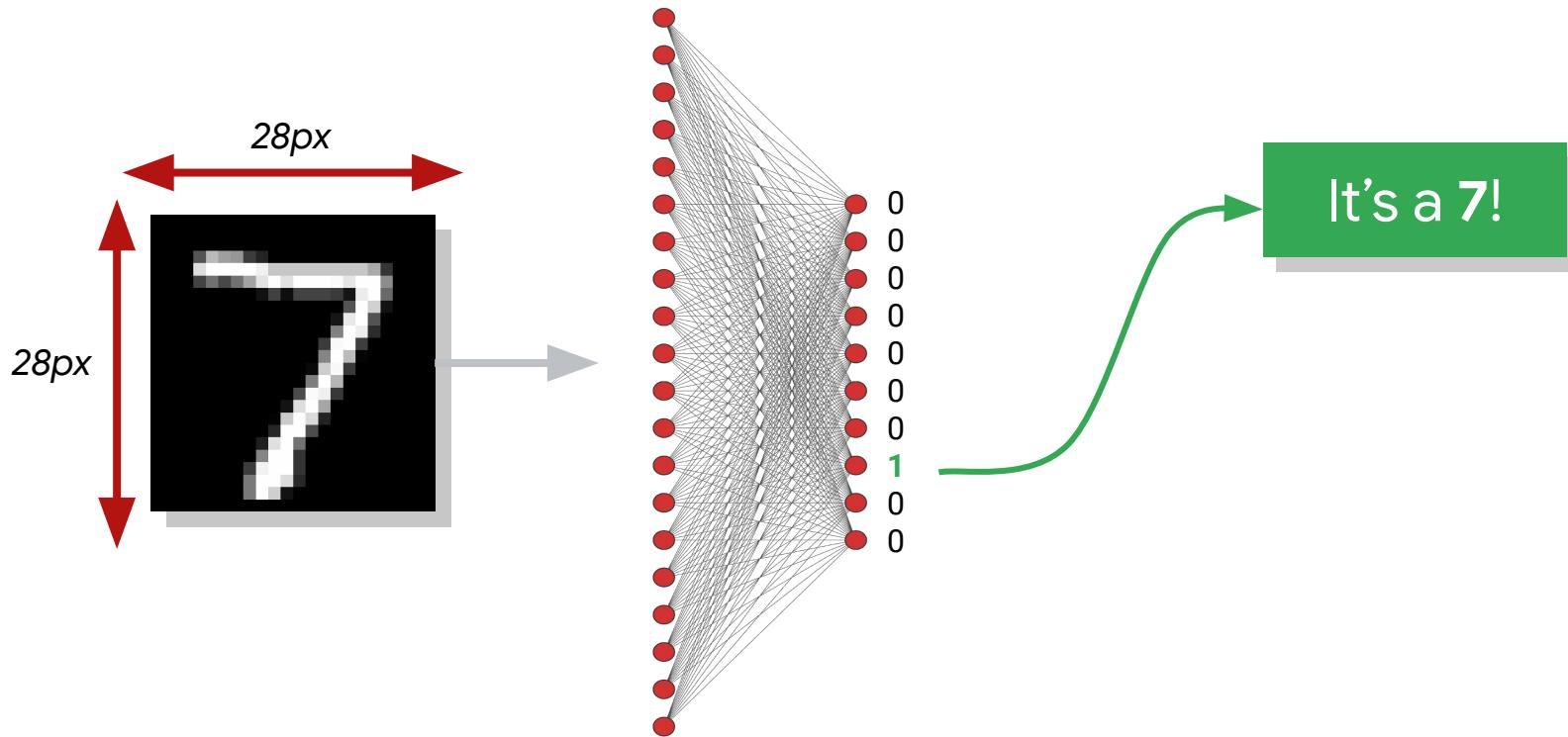
# Case Study: Handwriting



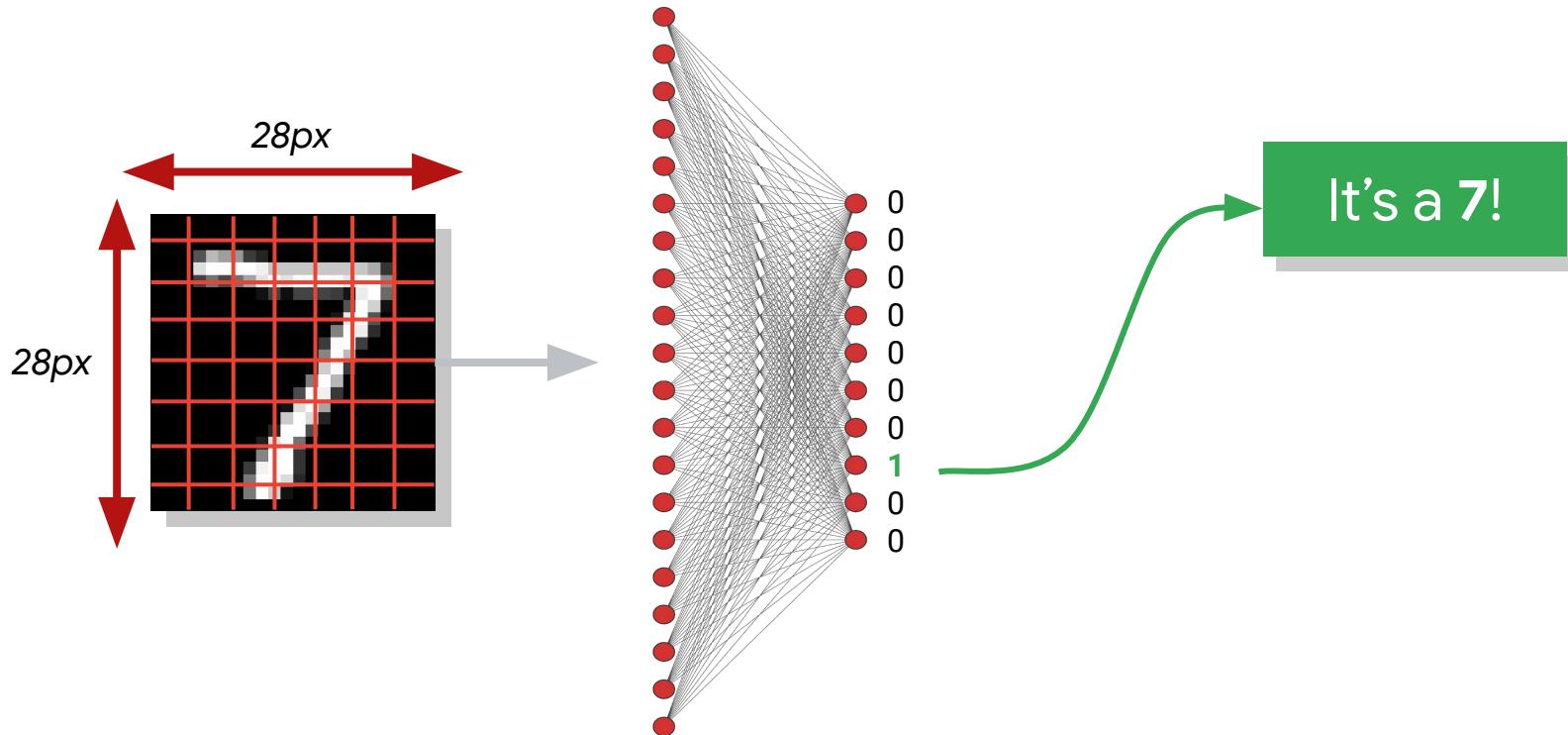
# What number?



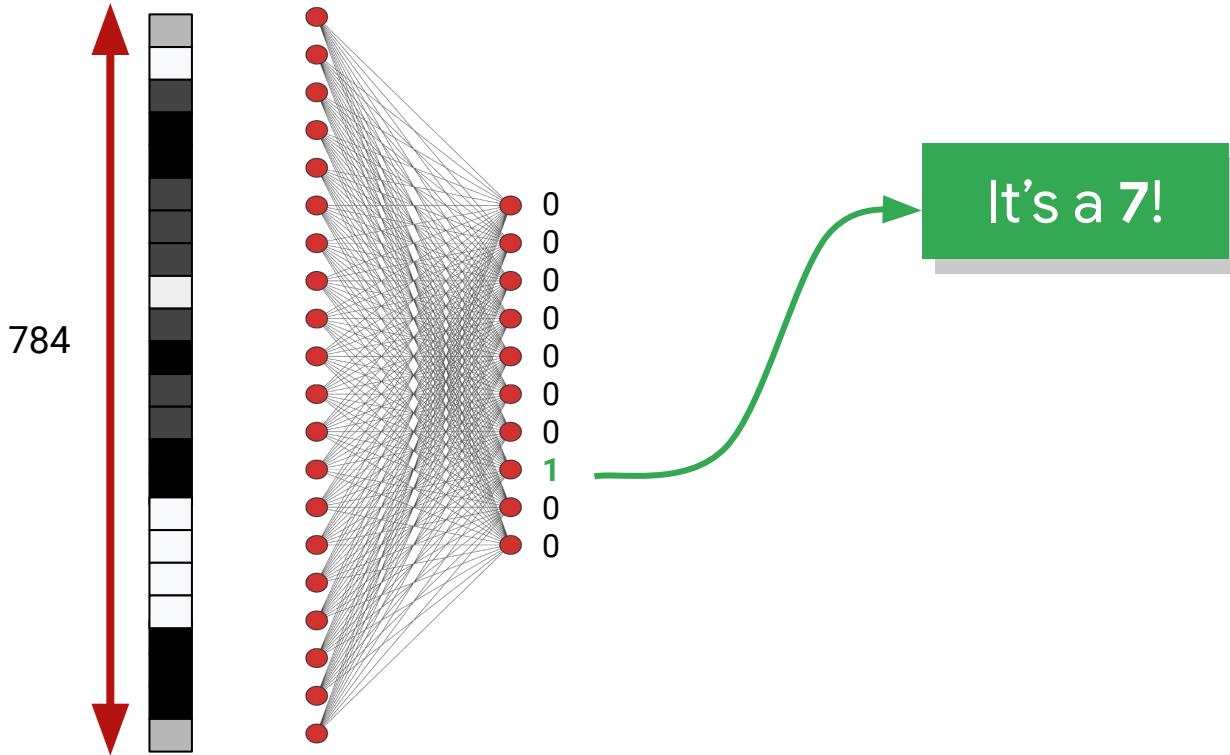
# What number?



# What number?



# Transform: flatten



# After Training the Model is VERY good!

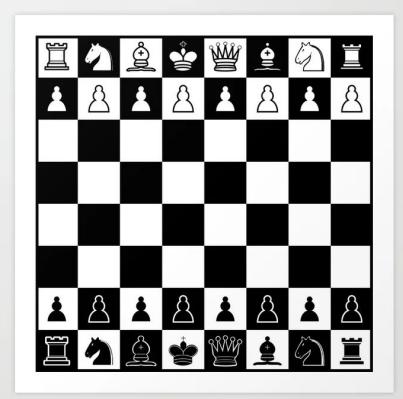
Rank	Model	Percentage↓ error	Accuracy	Trainable Parameters	Error rate	Percentage correct	Extra Training Data	Paper	Code	Result	Year	Tags
1	Однородный ансамбль с простым CNN	0.09	99.91				x	An Ensemble of Simple Convolutional Neural Network Models for MNIST Digit Recognition			2020	
2	Branching/Merging CNN + Homogeneous Vector Capsules	0.13	99.87	1,514,187			x	No Routing Needed Between Capsules			2020	
3	EnsNet (Ensemble learning in CNN augmented with fully connected subnetworks)	0.16	99.84				x	Ensemble learning in CNN augmented with fully connected subnetworks			2020	
4	Efficient-CapsNet	0.16	99.84	161,824			x	Efficient-CapsNet: Capsule Network with Self-Attention Routing			2021	
5	SOPCNN (Only a single Model)	0.17	99.83	1,400,000			x	Stochastic Optimization of Plain Convolutional Neural Networks with Simple methods			2020	
6	RMDL (30 RDLs)	0.18	99.82				x	RMDL: Random Multimodel Deep Learning for Classification			2018	
7	DropConnect	0.21	99.79				x	Regularization of Neural Networks using DropConnect			2013	

<https://paperswithcode.com/sota/image-classification-on-mnist>

# And it can solve problems we couldn't solve without ML!

## DeepBlue

On average in any board configuration there are **35** possible moves in chess.



# And it can solve problems we couldn't solve without ML!

## AlphaGo

“There are an astonishing **10 to the power of 170 possible board configurations** - more than the number of atoms in the known universe. This makes the game of Go a **googol times more complex than chess.**”

<https://www.deepmind.com/research/highlighted-research/alphago>

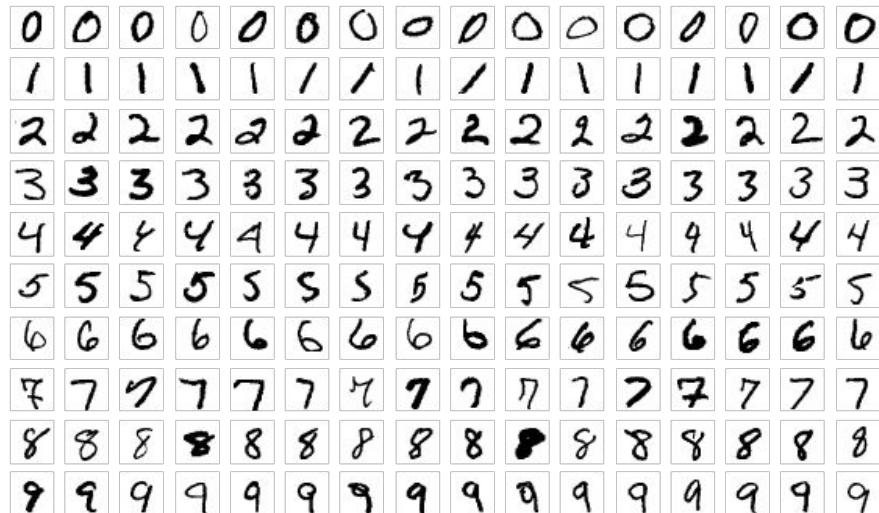
## DeepBlue

On average in any board configuration there are **35** possible moves in chess.



# But It Need Lots of Data

This is  
considered  
a **SMALL**  
and simple  
dataset  
(~45MB)



10 Classes

6000 Images / Class

# But It Need Lots of Data

GPT-3 Used  
~45TB of  
data that's  
~1,000,000  
times more  
data than  
**MNIST!**



# Today's Agenda

- What is Artificial Intelligence?
- Hands-on: AutoDraw
- What is (Deep) Machine Learning?
- Hands-on: ThingTranslator
- What is Responsible TinyML?
- Summary

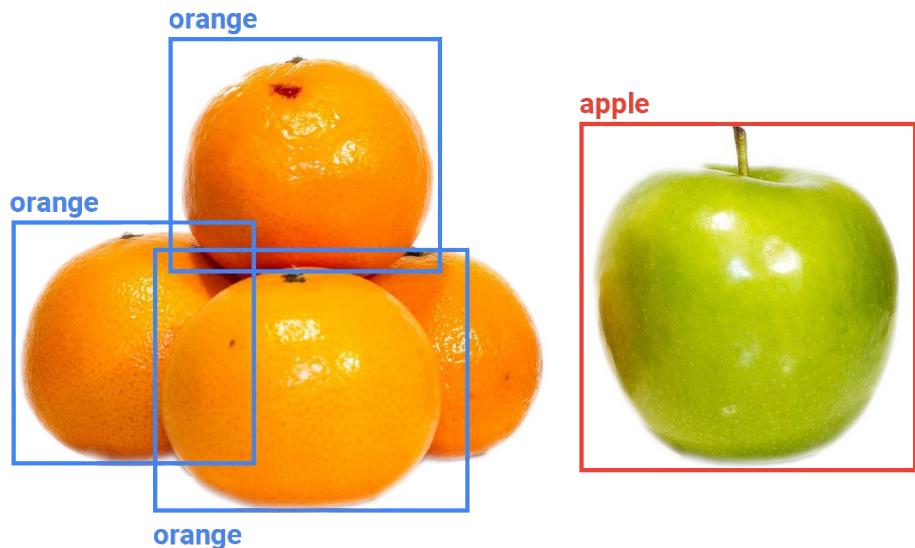
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# Thing Translator

This is an  
**A.I.**  
**Experiment**

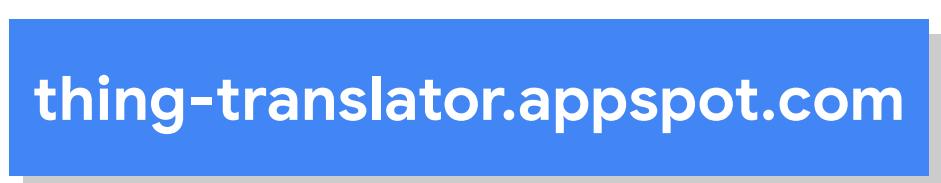
# Thing Translator



# Thing Translator



# Thing Translator



# Discussion Groups

1. Do you think the AI did a **good job?**  / 
2. **Why** do you think the AI **worked well**?
3. **How** did the AI solve this task? 
4. What types of things were **particularly hard or easy** for the AI?
5. Was the AI **better or worse** in this experiment? **Why** do you think?



anything else?

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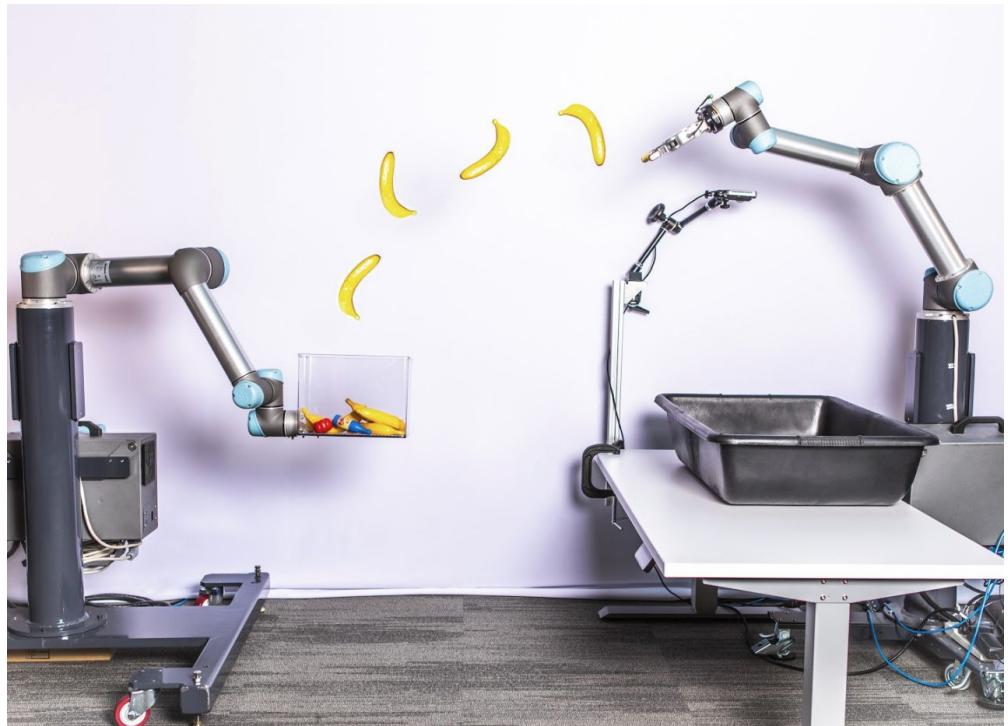
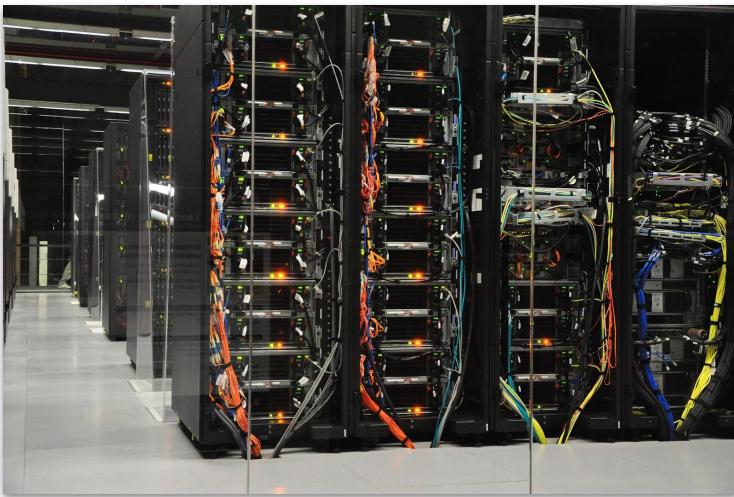
TinyML

ML

*What's the  
difference?*



# Cloud / Server



# Mobile



<https://plantvillage.psu.edu/>

# ML on Embedded Devices



IoT 1.0:  
Internet  
of Things



IoT 2.0:  
Intelligence  
on Things



# No Good Data Left Behind

**5 Quintillion**

bytes of data produced  
every day by IoT

**<1%**

of unstructured data is  
analyzed or used at all

IoT 1.0:  
**Internet**  
of Things



IoT 2.0:  
**Intelligence**  
on Things

B  
L  
E  
R  
P

IoT 1.0:  
**Internet**  
of Things



IoT 2.0:  
**Intelligence**  
on Things

**Bandwidth**  
**Latency**  
**Energy**  
**Reliability**  
**Privacy**

IoT 1.0:  
Internet  
of Things



IoT 2.0:  
Intelligence  
on Things

Bandwidth  
Latency  
Energy



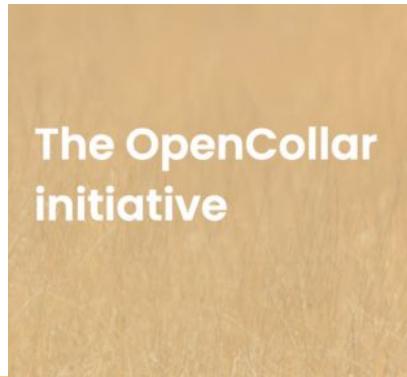
Battery Life is  
only O(months)  
and only sends  
GPS signal

IoT 1.0:  
Internet  
of Things



IoT 2.0:  
Intelligence  
on Things

# Bandwidth Latency Energy



IoT 1.0:  
**Internet**  
of Things



IoT 2.0:  
**Intelligence**  
on Things



Google Assistant



**Reliability**  
**Privacy**

IoT 1.0:  
Internet  
of Things



IoT 2.0:  
Intelligence  
on Things

Bandwidth  
Latency  
Energy  
Reliability  
Privacy

TinyML  
to  
the rescue!

# What is Tiny Machine Learning (**TinyML**)?

**TinyML**



Fastest-growing field of **ML**



# What is Tiny Machine Learning (**TinyML**)?

**TinyML**

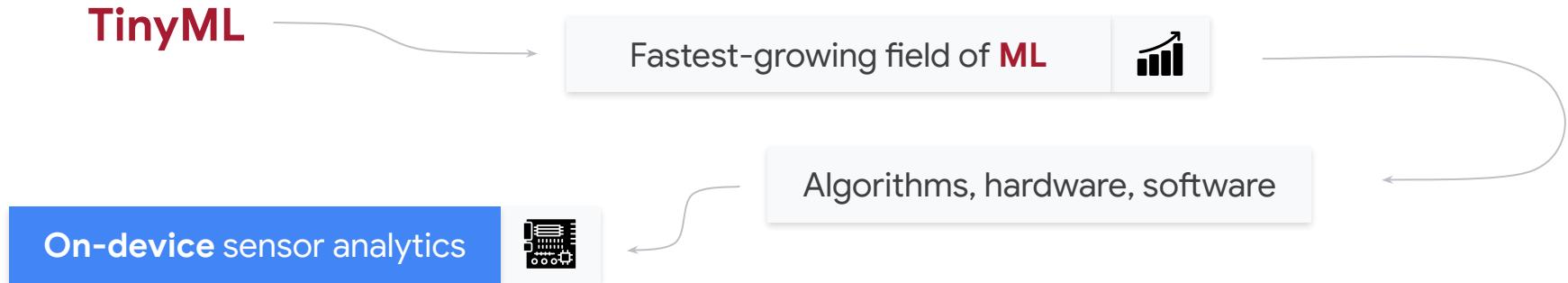
Fastest-growing field of **ML**



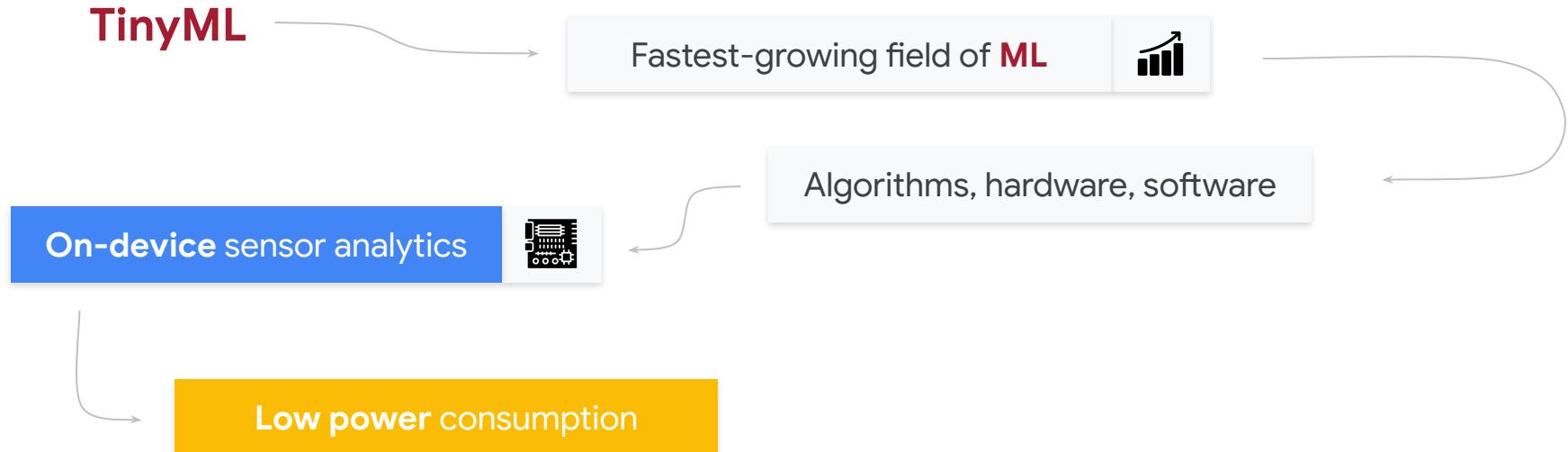
Algorithms, hardware, software



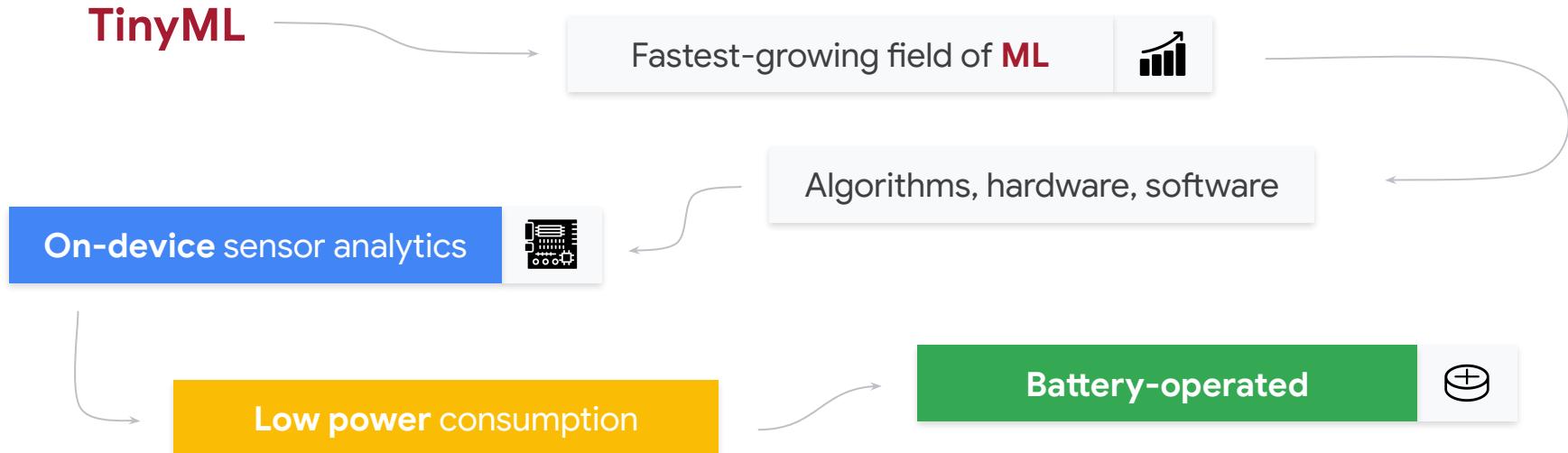
# What is Tiny Machine Learning (**TinyML**)?



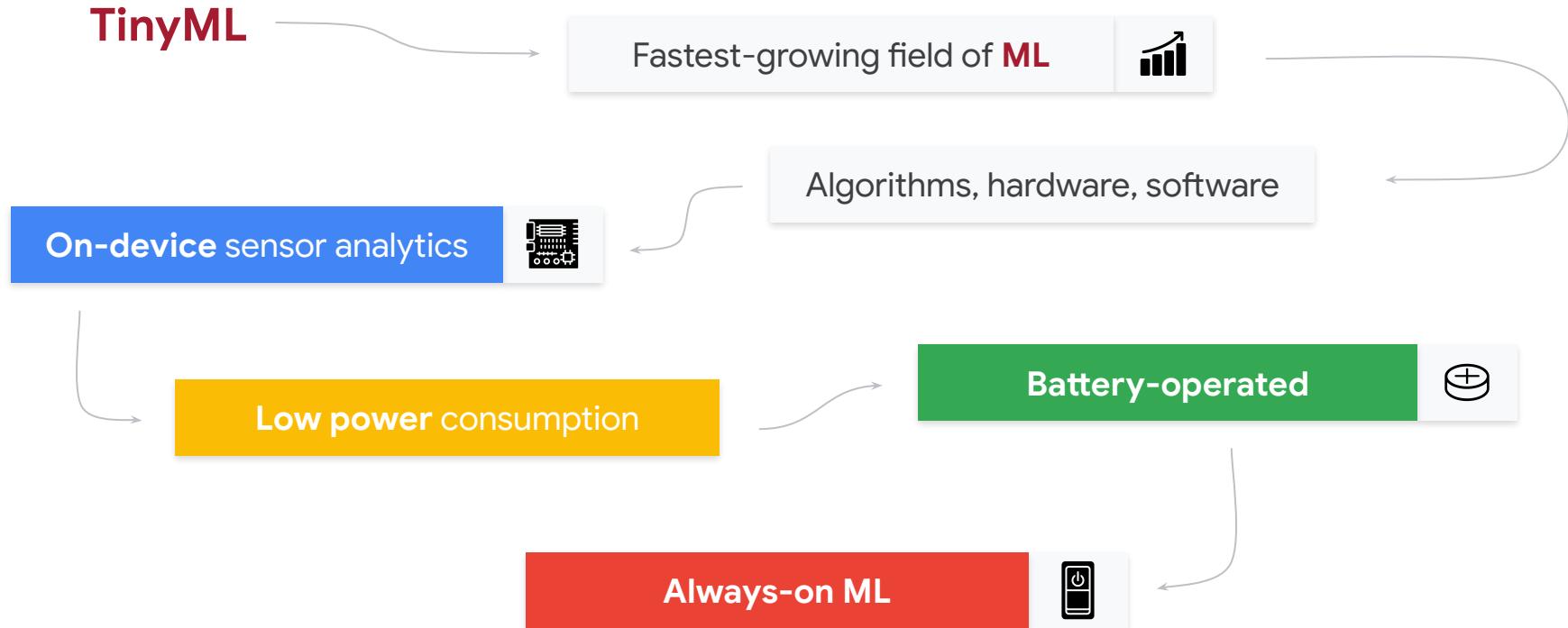
# What is Tiny Machine Learning (**TinyML**)?



# What is Tiny Machine Learning (**TinyML**)?



# What is Tiny Machine Learning (**TinyML**)?



# What is Tiny Machine Learning (**TinyML**)?

**TinyML**

Fastest-growing field of **ML**



On-device sensor analytics



Algorithms, hardware, software

## Putting ML on embedded devices!

Low power consumption

Battery-operated



Always-on ML





# Promising Social Applications of TinyML

Wildlife conservation

## ElephantEdge

Building The World's Most Advanced  
Wildlife Tracker.



Agriculture

May be able to reduce agrichemical use to 0.1%  
of conventional blanket spraying

## Technology: The Future of Agriculture

[Anthony King](#)

[Nature](#) 544, S21–S23 (2017) | [Cite this article](#)

161k Accesses | 132 Citations | 209 Altmetric | [Metrics](#)

F Meet TinyML: The Latest Mach... +

forbes.com/sites/sap/2021/11/08/meet-tinyml-the-latest-machine-learning-tech-having-a... ★ M L C Research TimeBuddy - CESMII - The S... AI Measurement a... Data Centric AI W... Other Bookmarks Reading List

Forbes

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Nov 8, 2021, 08:30am EST | 15,696 views

## Meet TinyML: The Latest Machine Learning Tech Having An Outsize Business Impact

Dr. Nicholas Nicolaidis Brand Contributor SAP BRANDVOICE | Paid Program Innovation

As device sensors proliferate across product development through insp... surfacing to provide actionable insi... There are sound economic reasons researchers predict IoT will have a trillion by 2025, identifying manufa... (trillion).



The rise of tinyML to collect data from edge devices is pretty much every indu...

“...we are in the midst of the digital revolution, and we are seeing the ultimate benefits of extreme energy efficiency, intelligence and analytics at low cost of features....”

EETimes - TinyML, Sees Big H... +

eetimes.com/tinyml-sees-big-h... tinyML Google MLC Research TimeBuddy CESMII - The S... AI Measurement a... Data Centric AI W... Other Bookmarks Reading List

EETimes

Machine learning at the edge: TinyML is getting big

MUST READ: Log4J flaw: Now state-backed hackers are using bug as part of attacks, researchers say

ZDNet Windows 11 5G Best VPNs Cloud Security AI Newsletters Blogs More Edition: US

## Machine learning at the edge: TinyML is getting big

Being able to deploy machine learning applications at the edge is the key to unlocking TinyML is the art and science of producing machine learning models frugal enough to rapid growth.



Written by **George Anadiotis**, Contributing Writer  
Posted in Big on Data on June 7, 2021 | Topic: Big Data

Is it \$61 billion and 38.4% CAGR by 2028 or \$43 billion and 37.4% CAGR by 2027? Depends on which report outlining the growth of [edge computing](#) you choose to go by, but in the end it's not that different.

What matters is that [edge computing is booming](#). There is growing interest by vendors, and [ample coverage](#), for good reason. Although the definition of [what constitutes edge computing](#) is a bit fuzzy, the idea is simple. It's about taking compute out of the data center, and bringing it as close to where the action is as possible.

Whether it's stand-alone IoT sensors, devices of all kinds, [drones](#), or [autonomous vehicles](#), there's one thing in common. Increasingly, data generated at the edge are used to feed applications powered by machine learning models. There's just one problem: machine learning models were never designed to be deployed at the edge. Not until now, at least. Enter [TinyML](#).

Tiny machine learning (TinyML) is broadly defined as a fast growing



What is machine learning?  
Everything you need to know

How TinyML is powering big ideas across critical industries.html +

tinyML Google MLC Research TimeBuddy CESMII - The S... AI Measurement a... Data Centric AI W... Other Bookmarks Reading List

Semiconductor Engineering

CIO DIGITAL ISSUE AWARDS EVENTS CIO THINK TANK NEWSLETTERS RESOURCES INSIDER SIGN IN REGISTER

Home

SAP NEXT EVOLUTION OF MACHINE LEARNING IS UPON US

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## How TinyML is powering big ideas across critical industries

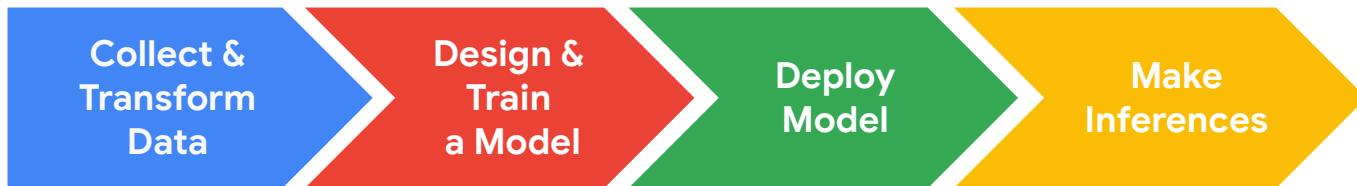
BrandPost Sponsored by SAP | [Learn More](#) | JUL 18, 2021 4:31 PM PDT



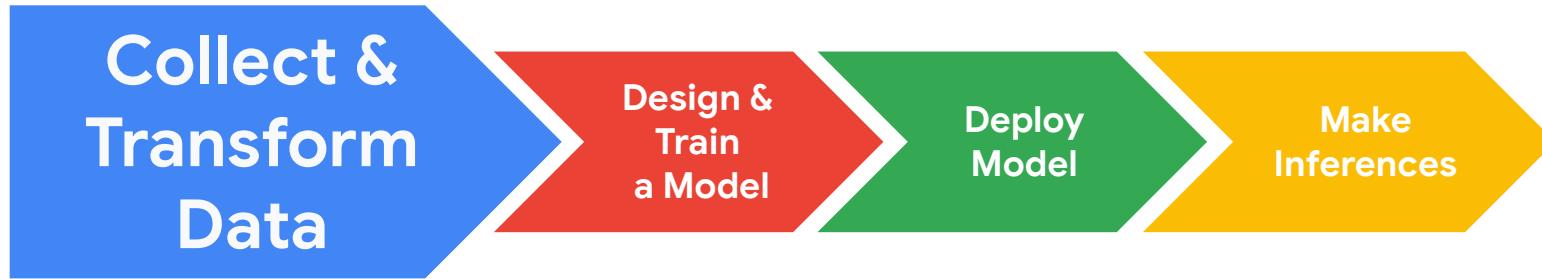
From cars and TVs to lightbulbs and doorbells. So many of the objects in everyday life have 'smart' functionality because the manufacturers have built chips into them.

But what if you could also run machine learning models in something as small as a golf ball dimple? That's the reality that's being enabled by TinyML, a broad movement to run tiny machine learning algorithms on embedded devices, or those with

# The (Tiny) Machine Learning Workflow

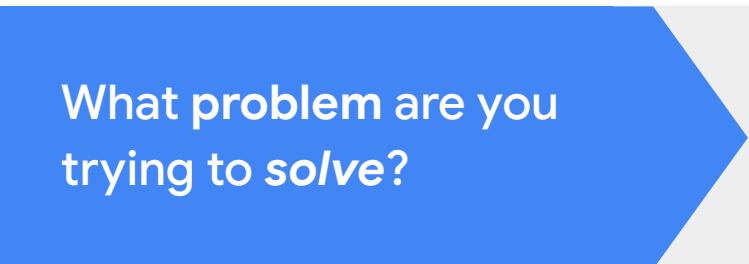


# The (Tiny) Machine Learning Workflow



If ML is going to be everywhere  
we need to consider how to best  
collect **GOOD** data **RESPONSIBLY**

# Good Data is Necessary for Accuracy



What problem are you trying to solve?

- Your data must contain useful features
- Can a human (expert) distinguish between examples of each class?
- How will you measure performance?

# Good Data is Necessary for Accuracy

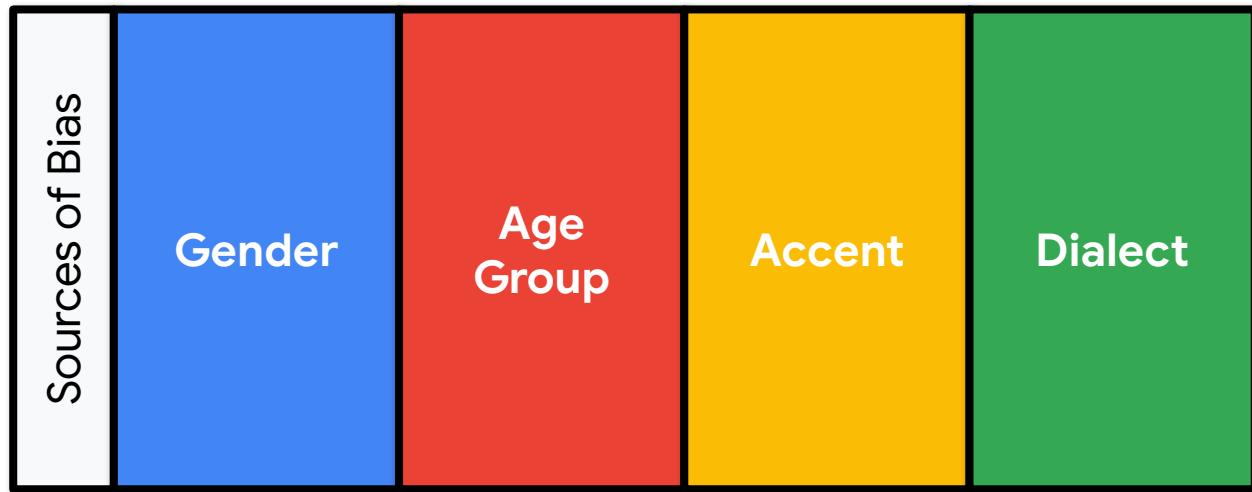
What problem are you  
trying to *solve*?

Both **quantity** and **quality**  
will influence your  
model's performance

- Your data must contain useful features
- Can a human (expert) distinguish between examples of each class?
- How will you measure performance?

- Wide variety of training examples
- Correct labels (answers)
- Good Balance (e.g., dog, cat, random)

# Potential **Bias** in Speech Recognition



Color Matters in Computer Vision

Facial recognition algorithms made by Microsoft, IBM and Face++ were more likely to misidentify the gender of black women than white men.



ARTIFICIAL INTELLIGENCE

## Predictive They need

Lack of transparency and bias is a problem. If we can't fix them, we're in trouble.

By Will Knight | TOM SIMONITE | BUSINESS

### The Best

US government to

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## Voice assistants seem to be worse at understanding commands from women



TECHNOLOGY 9 May 2019

By Nicole Kobi



> 7 percent of lighter-skinned females in a set of



> 12 percent of darker-skinned males in a set of



Gender was misidentified in 35 percent of darker-skinned females in a set of 271

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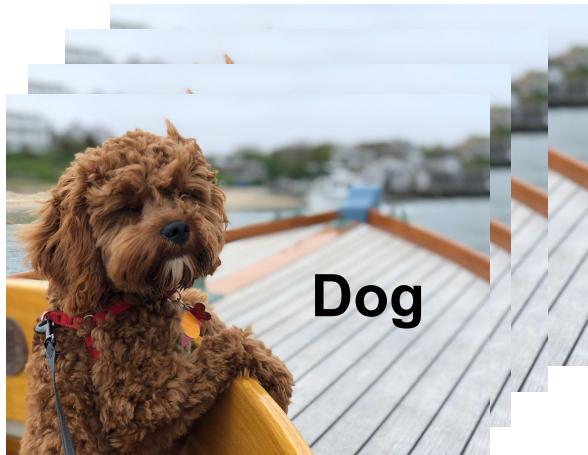
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# Machine Learning Workflow



# Machine Learning Workflow



INPUTS	LABELS
0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 4 4 4 4 4 4 4 4 4 4 4 4 4 4 5 5 5 5 5 5 5 5 5 5 5 5 5 5 6 6 6 6 6 6 6 6 6 6 6 6 6 6 7 7 7 7 7 7 7 7 7 7 7 7 7 7 8 8 8 8 8 8 8 8 8 8 8 8 8 8 9 9 9 9 9 9 9 9 9 9 9 9 9 9	0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 3 3 3 3 3 3 3 3 3 3 3 3 3 4 4 4 4 4 4 4 4 4 4 4 4 4 4 5 5 5 5 5 5 5 5 5 5 5 5 5 5 6 6 6 6 6 6 6 6 6 6 6 6 6 6 7 7 7 7 7 7 7 7 7 7 7 7 7 7 8 8 8 8 8 8 8 8 8 8 8 8 8 8 9 9 9 9 9 9 9 9 9 9 9 9 9 9

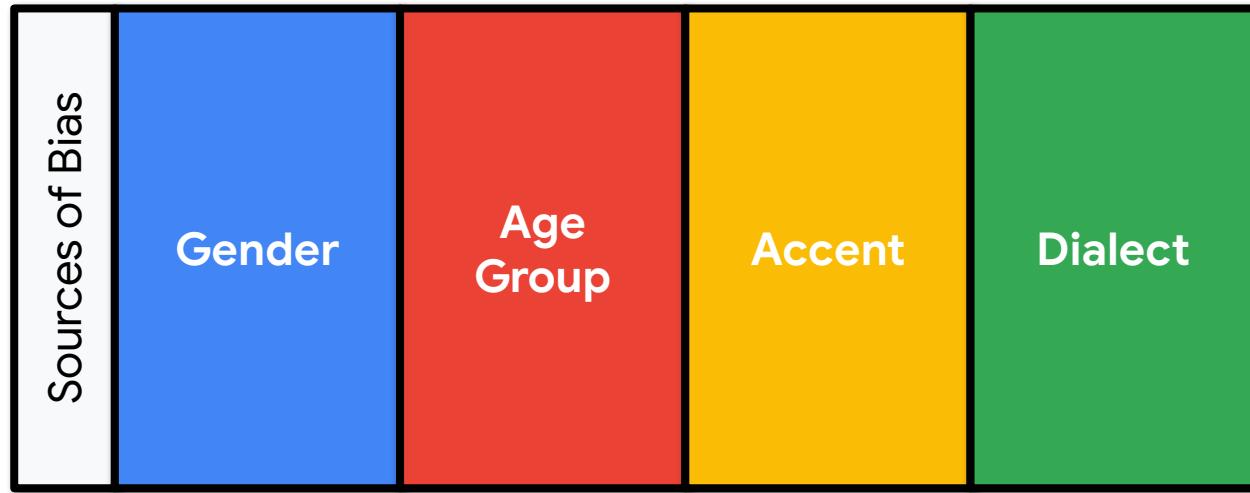
Collect &  
Transform Data

Design & Train  
a Model

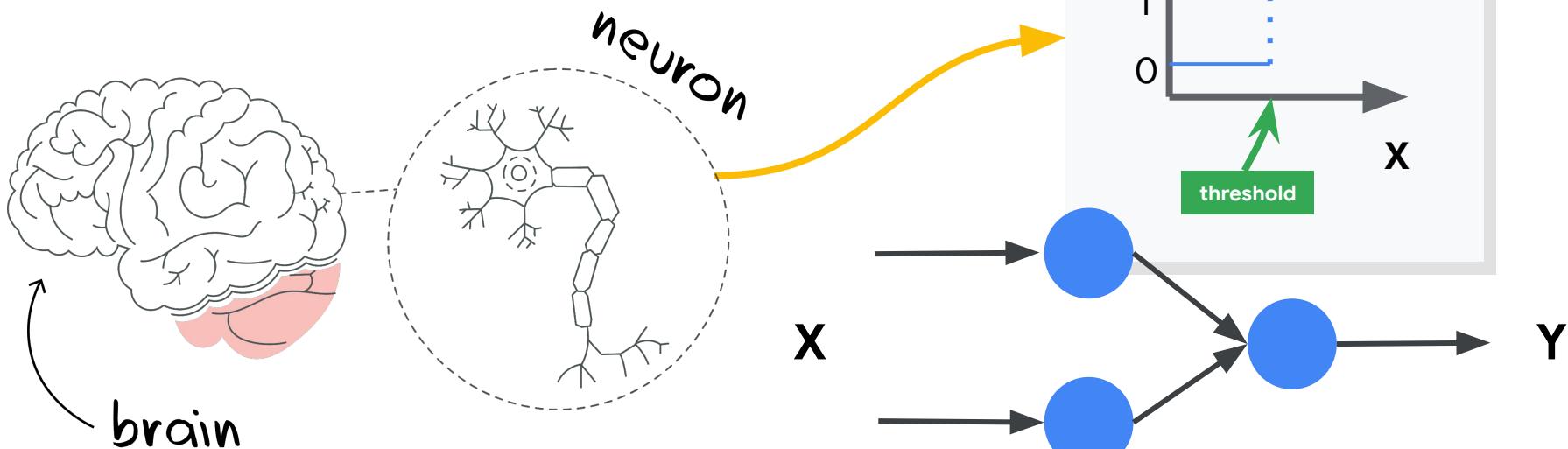
Deploy  
Model

Make  
Inferences

# Machine Learning Workflow



# Machine Learning Workflow



Collect &  
Transform Data

Design & Train  
a Model

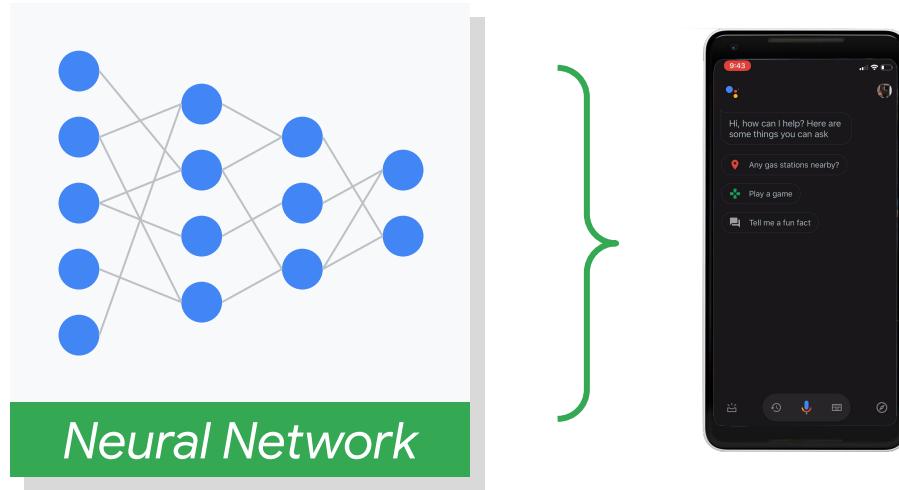
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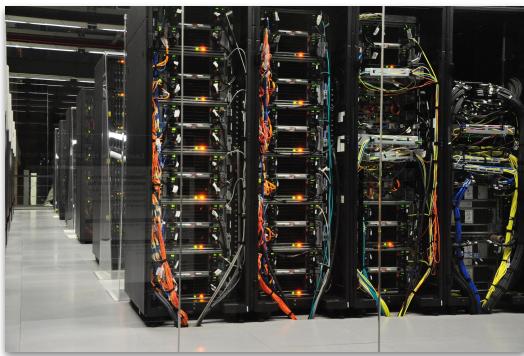
# Machine Learning Workflow



# Machine Learning Workflow



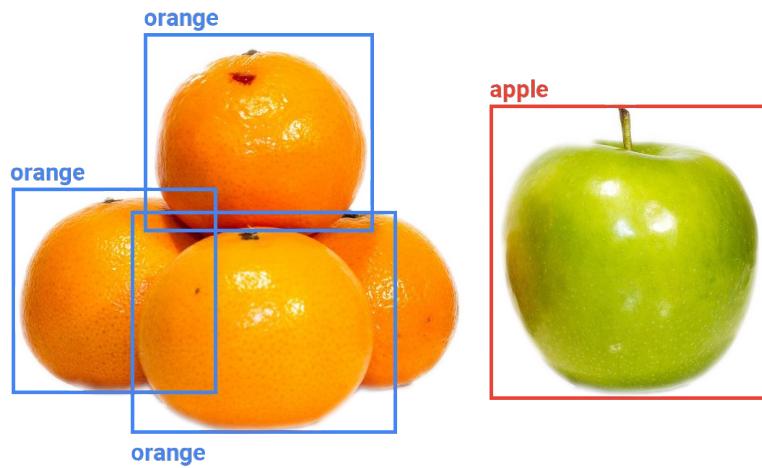
# Machine Learning Workflow



Google  
Assistant



# Machine Learning Workflow



# Our website!

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[tinyMLEdu.org/EASI-22](https://tinyMLEdu.org/EASI-22)

home base for **all information!**



---

hágoónee' 🙌

see you again at 12pm (Mountain Time)