

# The Machine Learning Taxonomy

Organizing 40+ Tasks by their Mathematical Roots

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# Before We Begin: A Simple Question

You use machine learning **every single day**.

Can you identify where?

## YOUR DAILY LIFE

Morning: Phone unlocks with your face

Commute: Google Maps predicts traffic

Email: Gmail filters spam, suggests replies

Music: Spotify recommends songs you'll love

Shopping: Amazon shows "You might also like..."

Photos: Google Photos groups by faces, finds "beach"

Evening: Netflix suggests what to watch

Chat: You ask ChatGPT a question

**Each of these is a different ML task!**

# The Big Insight

Every ML task boils down to **one question**:

"What are you trying to PREDICT?"

## Predicting a Category?

→ Classification

*"Is this email spam?"*

## Predicting a Number?

→ Regression

*"What will be the price?"*

## Predicting a Sequence?

→ Seq2Seq

*"How do you say this in French?"*

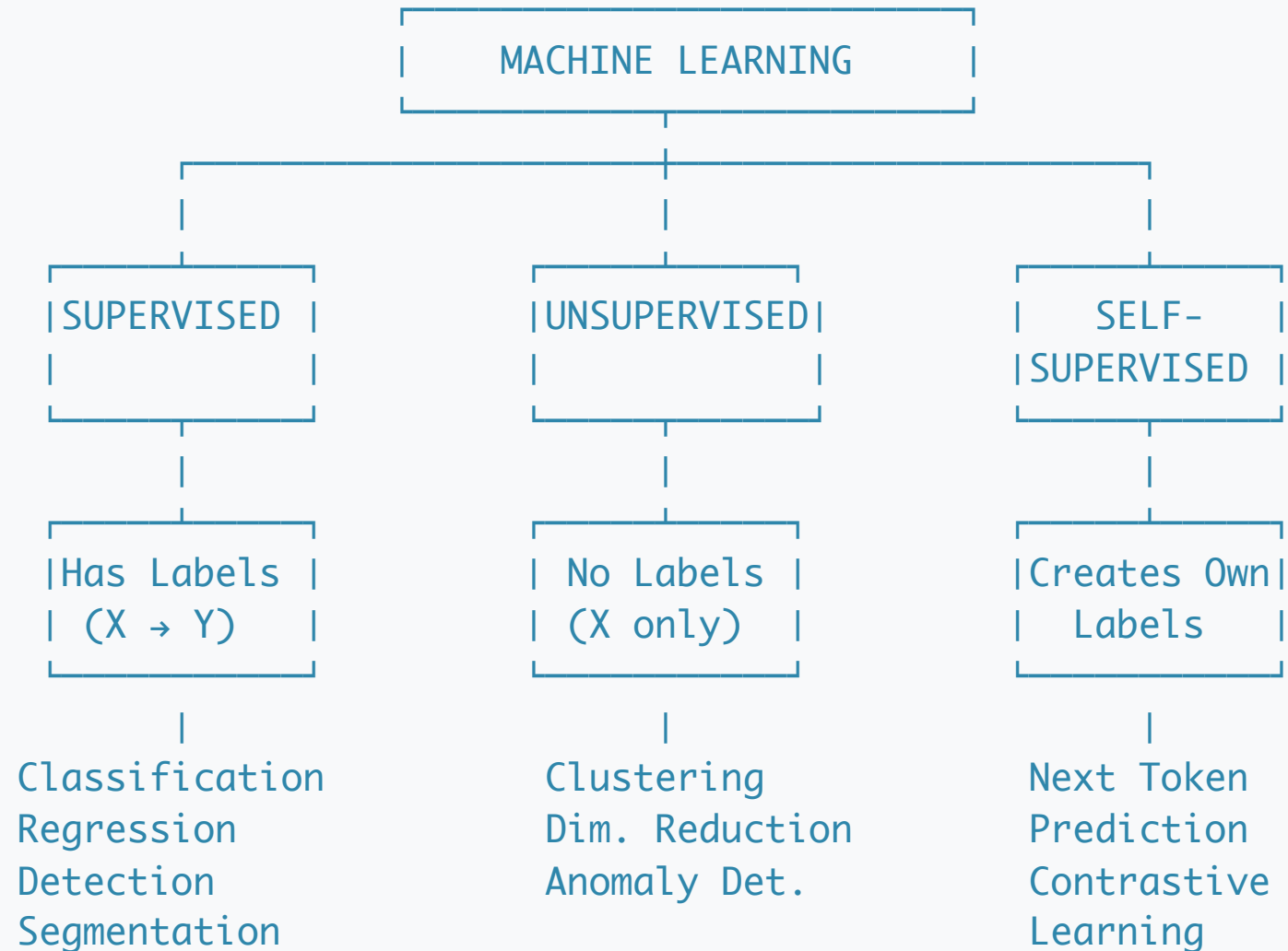
## Creating Something New?

→ Generative

*"Draw me a cat in space"*

Once you know the "output type", you know which family the task belongs to!

# The Master Taxonomy



# Section 1: Classification

"Which Bucket Does This Belong To?"

# Classification: You Already Know This!

Think about how YOU classify things every day:

```
"Is this mushroom safe to eat?"    → Edible / Poisonous
```

```
"What animal is in this photo?"    → Dog / Cat / Bird
```

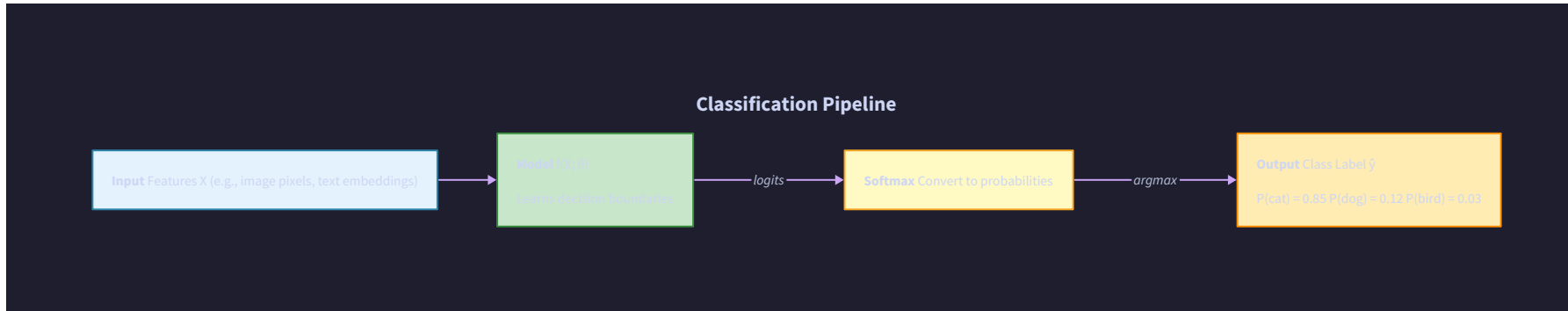
```
"Should I trust this email?"       → Legitimate / Spam
```

```
"What number is written here?"     → 0 / 1 / 2 / ... / 9
```

You look at the input and pick **one category** from a fixed set.

That's classification!

# Classification: The Core Idea



The model learns patterns that distinguish categories, then applies those patterns to new inputs.

# Example: How Does Email Spam Detection Work?

## Step 1: TRAINING (Learning from examples)

Email: "Meeting at 3pm tomorrow"	Label: NOT SPAM
Email: "You won \$1,000,000! CLICK NOW!!!"	Label: SPAM
Email: "Your Amazon order has shipped"	Label: NOT SPAM
Email: "Hot singles in your area"	Label: SPAM
... (millions more examples)	
Model learns: ALL CAPS, "won", "click", "\$\$\$" → probably SPAM	
Normal sentences, known senders → probably OK	

## Step 2: INFERENCE (Using the model)

New email: "CONGRATULATIONS! You're selected for a FREE gift!"

Model thinks: ALL CAPS ✓, "FREE" ✓, excitement ✓

Prediction: SPAM (95% confident)



# Binary vs Multi-Class Classification

## Binary Classification

*Two possible outcomes*

Input: Tumor image

Output:

- ☐ Benign
- ☒ Malignant

(Only 2 choices)

Examples:

- Spam / Not Spam
- Fraud / Legitimate
- Pass / Fail
- Yes / No

## Multi-Class Classification

*Many possible outcomes*

Input: Animal photo

Output:

- ☐ Dog
- ☐ Cat
- ☒ Bird ← Winner!
- ☐ Fish
- ☐ Horse

(Many choices, pick ONE)

Examples:

- Digit recognition (0-9)
- ImageNet (1000 classes)
- Emotion detection (6+)

# Multi-Label Classification

**Wait, what if something belongs to MULTIPLE categories?**

Movie Classification:

Input: "The Avengers"

Binary/Multi-class would say: "Action" (pick one!)

But actually it's:

- ✓ Action
- ✓ Sci-Fi
- ✓ Adventure
- Romance
- Documentary

(Multiple labels can be TRUE at once!)

## **Real-world multi-label examples:**

- News article topics (Politics AND Economy AND International)
- Product categories (Electronics AND Computers AND Accessories)

# The Math Behind Classification

Input  $x$   $\rightarrow$  Neural Network  $\rightarrow$  Softmax  $\rightarrow$  Probabilities

|



	Cat:	0.85	
	Dog:	0.10	
	Bird:	0.05	

|

Sum = 1.0

|



Pick highest

|



"Cat"

**Softmax** converts raw scores to probabilities that sum to 1.

The model isn't just saying "Cat" — it's saying "85% sure it's a cat!"

# Classification: Real-World Examples

Application	Input	Output	Impact
Face Unlock	Selfie	"Is this the owner?"	Security
Medical X-ray	Image	Healthy/Pneumonia/COVID	Healthcare
Credit Approval	Application	Approve/Deny	Finance
Sentiment	Tweet	Positive/Negative/Neutral	Marketing
Plant Disease	Leaf photo	38 disease types	Agriculture
Quality Control	Product photo	Pass/Fail	Manufacturing

Classification is everywhere! It's the "Hello World" of machine learning.

## Section 2: Regression

"How Much? How Many?"

# Regression: When the Answer is a Number

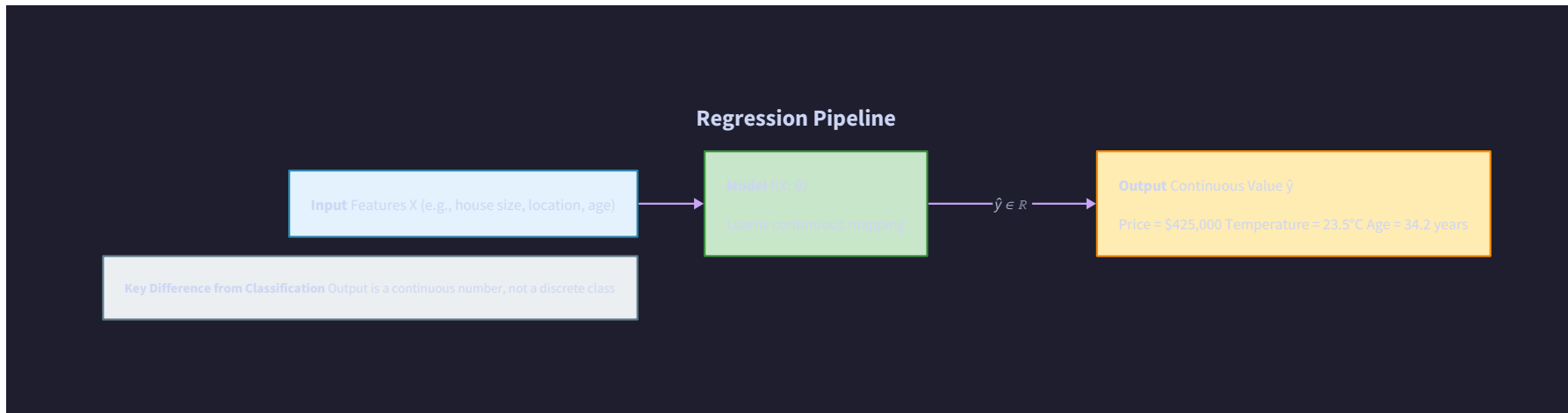
Classification: *"Which category?"* → Discrete answer

Regression: *"How much?"* → Continuous number

"How old is this person?"	→ 27.3 years
"What's this house worth?"	→ \$425,000
"How many units will sell?"	→ 1,247 units
"What temperature tomorrow?"	→ 28.5°C
"How long until the bus arrives?"	→ 7.2 minutes

The output is **any number** on a continuous scale!

# Regression: The Core Idea



Instead of choosing from buckets, we predict a specific point on a number line.

# Example: House Price Prediction

FEATURES (Input):

PREDICTION (Output):

Bedrooms:	3	
Bathrooms:	2	
Square Feet:	1,500	
Year Built:	2005	
Location Score:	8.5/10	
Has Pool:	No	



\$425,000

The model learns patterns like:

- More bedrooms → higher price (usually)
- Better location → higher price (definitely!)
- Older house → lower price (sometimes)
- Has pool → depends on the climate!

Then combines all these patterns into ONE number.



# Regression is Actually Everywhere!

You might think you're looking at classification, but often it's regression:

## BOUNDING BOX DETECTION

DOG

← This box needs  
4 numbers:

$x = 50$  (left edge) ← Regression!

$y = 30$  (top edge) ← Regression!

$w = 100$  (width) ← Regression!

$h = 80$  (height) ← Regression!

DETECTION = Classification (what?) + Regression (where?)

# Classification vs Regression: Side by Side

## CLASSIFICATION

Input → Model → [0.1, 0.2, 0.7] → Class "C"

▲  
Probabilities  
must sum to 1

Loss Function: Cross-Entropy (compares probability dists)

## REGRESSION

Input → Model → 425000.00 → \$425,000

▲  
Any real number  
(no constraints)

Loss Function: MSE / MAE (measures distance from true value)

# The Confusion: Age Prediction

Is predicting someone's age classification or regression?

## OPTION A: Classification (Age Groups)

- Child (0-12)
- Teenager (13-19)
- Adult (20-59)
- Senior (60+)

Loses information!  
"25" and "55" are same class

## OPTION B: Regression (Exact Age)

Prediction: 27.3 years

More precise!  
But harder to predict exactly

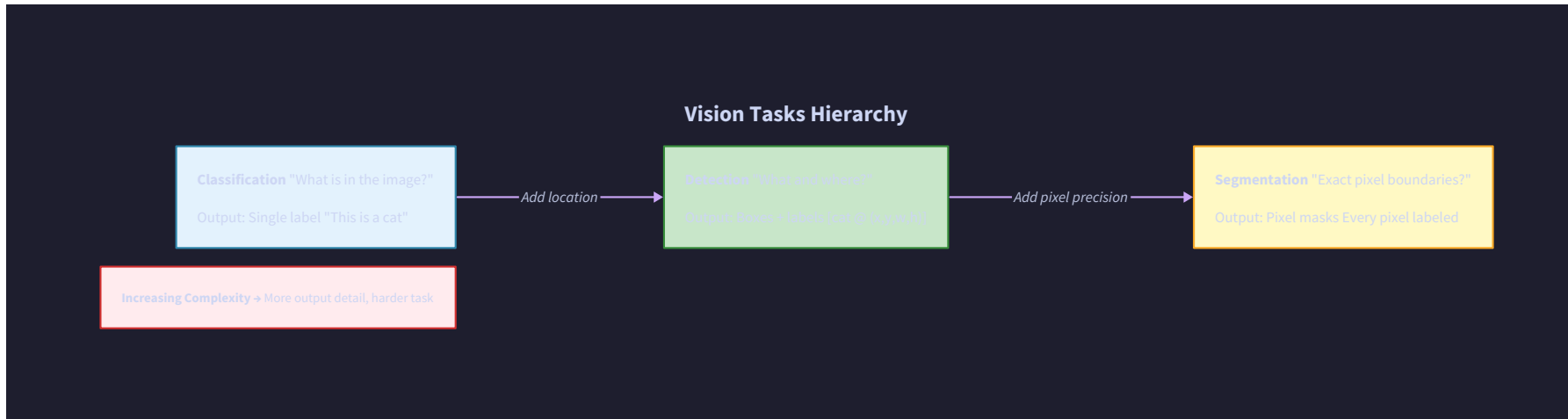
The choice depends on your application! For ID verification: regression. For marketing segments: classification might be enough.

# Section 3: Vision Hierarchy

From Labels to Pixels

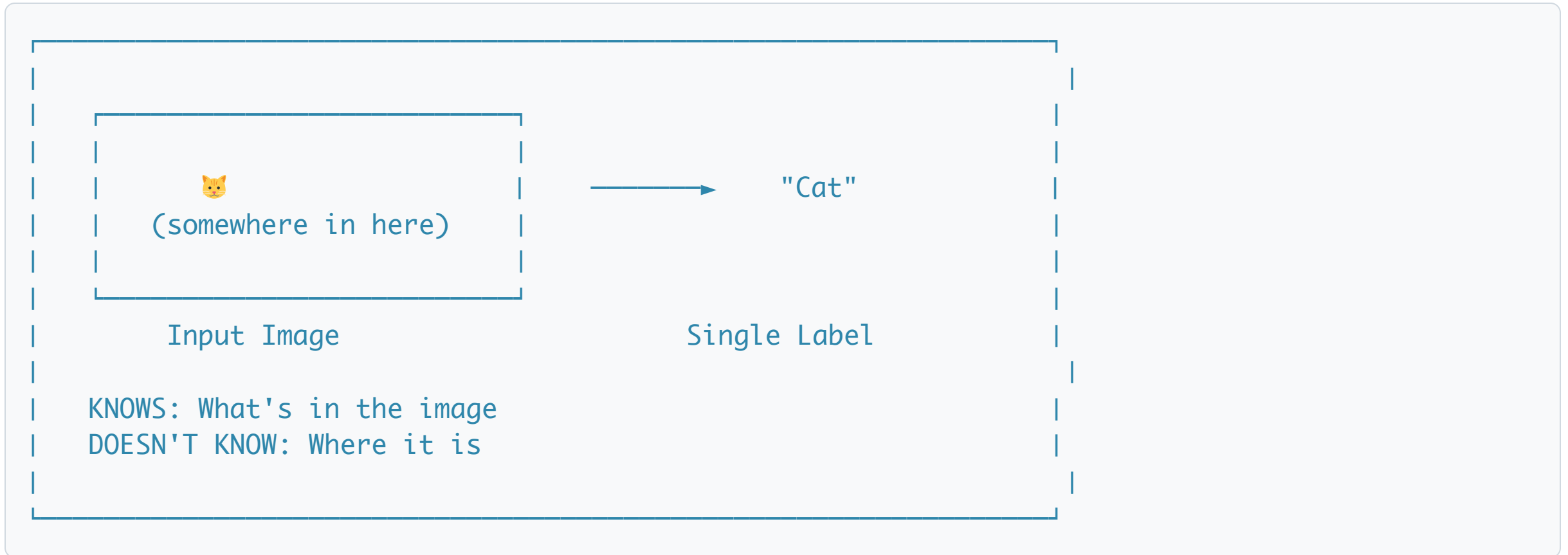
# The Computer Vision Ladder

Each level gives you **more information** about what's in the image:



Each level builds on the previous. More precision = More complexity = More data needed.

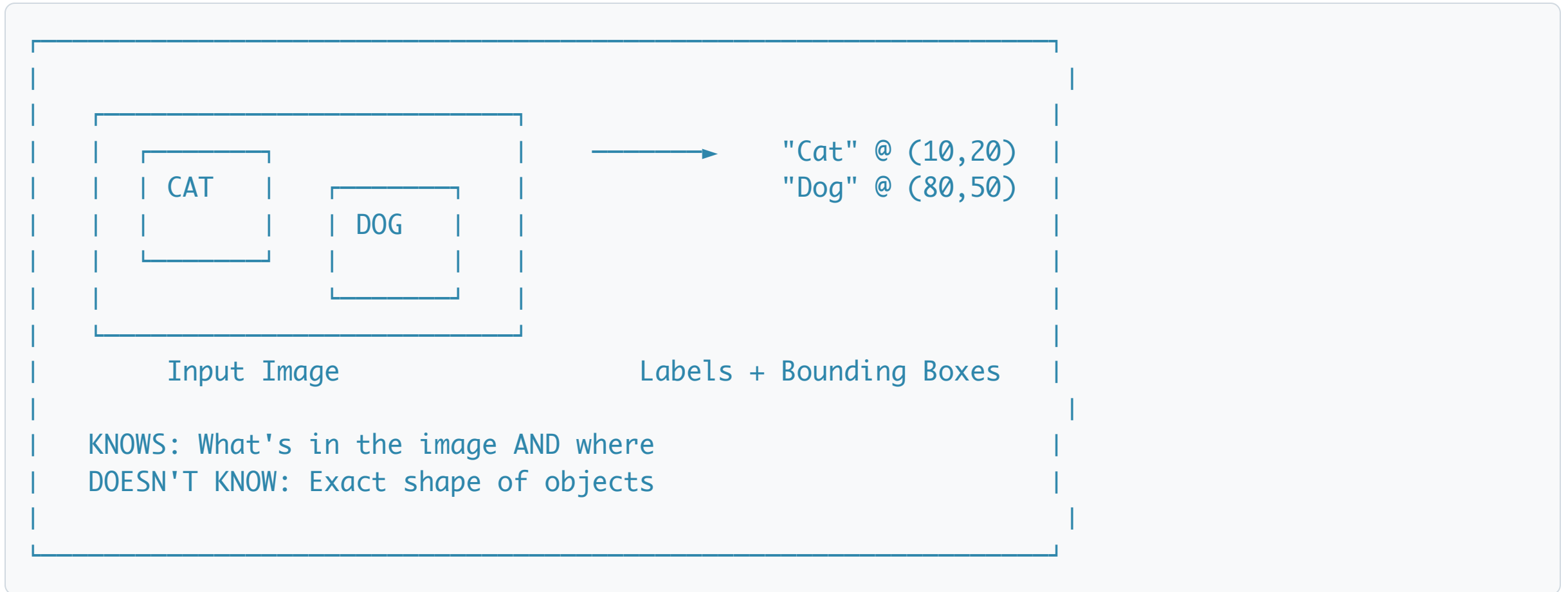
# Level 1: Image Classification



## Use Cases:

- Google Photos: "Show me all photos with dogs"
- Medical: "Is this X-ray normal or abnormal?"
- Quality Control: "Is this product defective?"

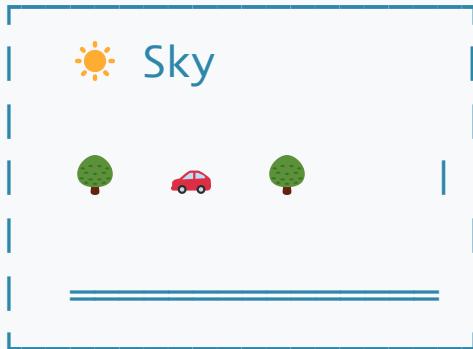
## Level 2: Object Detection



**Detection = Classification (what) + Regression (where)**

# Level 3: Semantic Segmentation

Input Image:



Output Mask:



EVERY pixel gets a class label!

Perfect for self-driving cars, medical imaging



# Level 4: Instance Segmentation

What if there are TWO cars?

SEMANTIC SEGMENTATION:

CCCCC	CCCCC
CCCCC	CCCCC

Both labeled "Car"

INSTANCE SEGMENTATION:

11111	22222
11111	22222

Car #1 vs Car #2

Semantic: "These pixels are CAR"

Instance: "These pixels are CAR #1, those are CAR #2"

Self-driving cars need Instance Segmentation — they must track WHICH car is doing what!

# Real-World Vision Hierarchy Example

## AUTONOMOUS DRIVING

Classification: "There are cars and people in this scene"  
(Not enough! Where are they?)

Detection: "Car at (100,200), Person at (300,150)"  
(Better! But how close to lane?)

Segmentation: "The drivable road area is these pixels"  
(Great! Now I know where to drive)

Instance Seg: "This is Car #1, that is Car #2, tracking..."  
(Perfect! I can predict each car's movement)

# Section 4: Sequence Tasks

When Order Matters

# Why Sequences Are Special

Some data comes in **ordered** form where **position matters**:

TEXT: "I love you" vs "You love I"  
(Sweet) (Grammatically wrong!)

DNA: ATCGATCG vs GATCATCG  
(Different gene!)

AUDIO: ♪ Do-Re-Mi vs ♪ Mi-Re-Do  
(Different melody!)

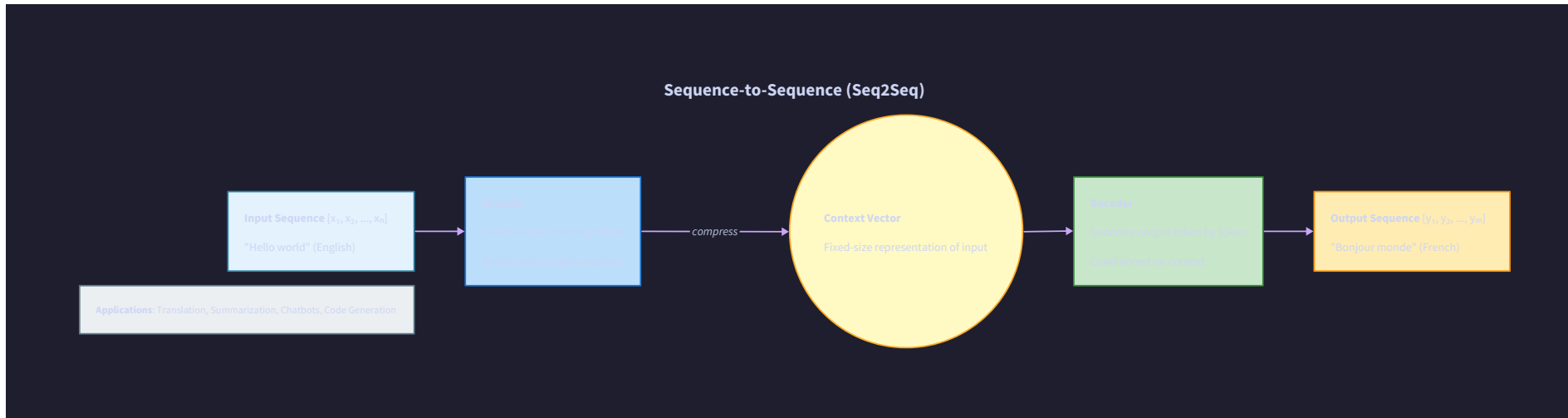
VIDEO: Frame1→Frame2→Frame3 vs Frame3→Frame2→Frame1  
(Forward vs Backward!)

For sequences, we need models that understand ORDER, not just content!

# Sequence-to-Sequence (Seq2Seq)

**Input sequence** → **Model** → **Output sequence**

(Lengths can be DIFFERENT!)



# Seq2Seq Examples

Task	Input	Output	Notes
Translation	"Hello, how are you?"	"Bonjour, comment allez-vous?"	Different lengths!
Summarization	Long article (1000 words)	Short summary (50 words)	Compression
Speech-to-Text	5 seconds of audio	"Hello world"	Modality change
Text-to-Speech	"Hello world"	5 seconds of audio	Reverse direction
Code Generation	"Sort this list"	<code>list.sort()</code>	Natural → Code
Chatbot	"What's 2+2?"	"The answer is 4"	Q&A

Google Translate, Siri, Alexa, ChatGPT — all use Seq2Seq!

# Token-Level Classification (Tagging)

Sometimes we classify **each element** in the sequence:

Input:	"Sundar	Pichai	visited	New	York	yesterday"
	▼	▼	▼	▼	▼	▼
Output:	PER	PER	0	LOC	LOC	0
PER = Person Name						
LOC = Location						
0 = Other (not an entity)						

This is **Named Entity Recognition (NER)**.

Think of it as "semantic segmentation for text" — every word gets a label!

# Section 5: Unsupervised Learning

## Finding Patterns Without Labels



# The Unsupervised Setting

## SUPERVISED:

Data: X (features)
Labels: Y (answers)
Learn: $f(X) \rightarrow Y$
"Teach by example"

## UNSUPERVISED:

Data: X (features)
Labels: NONE!
Find: patterns in X
"Learn by exploration"

**No one tells the model what to look for — it discovers structure on its own!**

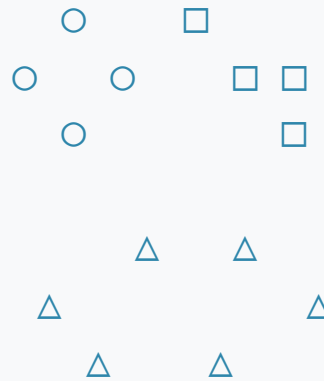
# Clustering: Finding Natural Groups

BEFORE (Unlabeled data):



No one told the algorithm these are 3 groups – it figured it out!

AFTER (Discovered clusters):



The algorithm discovered 3 natural groupings.

## Real applications:

- Customer segmentation: VIPs vs Bargain hunters vs Occasional buyers
- Gene expression: Which genes behave similarly?
- Document clustering: Group news articles by topic

# Dimensionality Reduction

**Problem:** High-dimensional data is hard to visualize and process.

Original: 1000-dimensional data  
(Can't visualize 1000 axes!)

```
[0.23, 0.11, 0.87, 0.45, 0.32, ... 1000]
```

PCA / t-SNE

```
[0.45, -0.23] ← Just 2D!
```

Can now plot it!



← Cluster 1

← Cluster 2

← Cluster 3

# Anomaly Detection

Find the weird ones.

Normal Transaction Pattern:



## Applications:

- Credit card fraud detection
- Network intrusion detection
- Manufacturing defect detection
- Medical abnormality detection

# Section 6: Generative Models

## Creating New Data

# Generative vs Discriminative

DISCRIMINATIVE (What we've seen so far):

[Image of cat] → Model → "Cat" or "Dog"

Given X, predict Y (which category)  
"What IS this?"

GENERATIVE (The magic):

"Draw a cat" → Model → [NEW image of a cat!]  
or just noise

Create NEW X from scratch  
"Make something that LOOKS LIKE this"

# The Generative AI Revolution

TEXT GENERATION (ChatGPT, Claude)

Prompt: "Write a poem about AI"

Output: "In silicon dreams, we think and grow..."

IMAGE GENERATION (DALL-E, Midjourney, Stable Diffusion)

Prompt: "A cat wearing a tiny hat, oil painting style"

Output: [Beautiful AI-generated artwork!]

MUSIC GENERATION (Suno, Udio)

Prompt: "Upbeat pop song about summer"

Output: ♪ [Complete song with lyrics!]

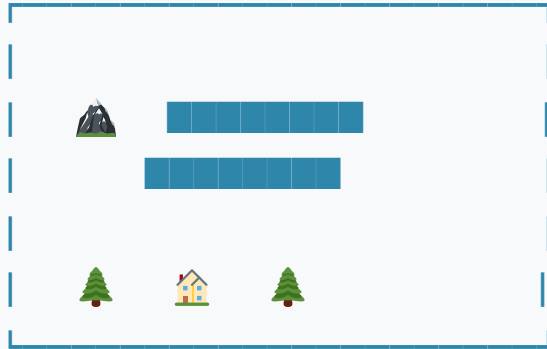
VIDEO GENERATION (Sora, Runway)

Prompt: "A dog running through a meadow, slow motion"

Output: [Realistic video that never existed!]

# Image Inpainting: Fill in the Blanks

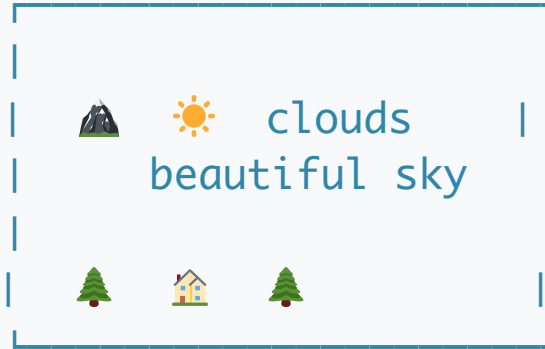
Original with hole:



(hole in image)



AI-filled result:



(AI filled it in!)

## Applications:

- Remove unwanted objects from photos
- Restore damaged/old photographs
- Extend images beyond their borders



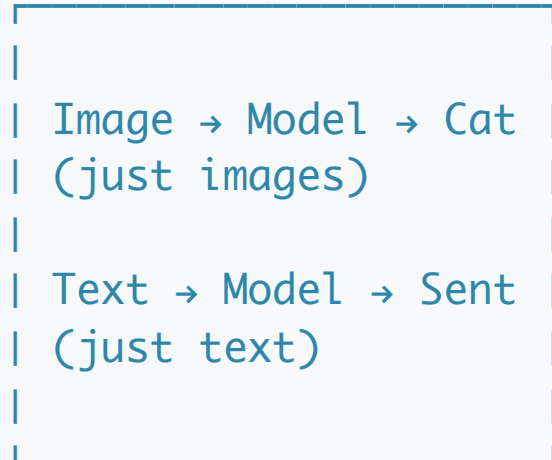
# Section 7: Multimodal & Complex Tasks

## Combining Everything

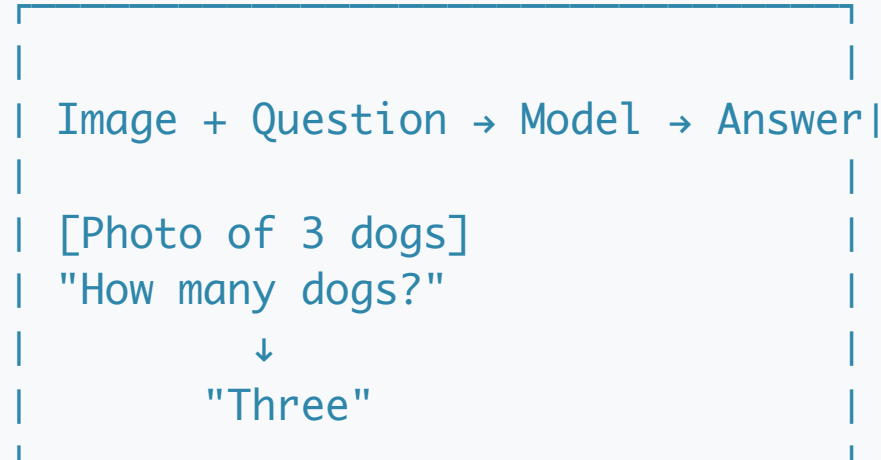
# Multimodal = Multiple Modalities

**Modalities:** Text, Image, Audio, Video, etc.

SINGLE-MODAL :



MULTI-MODAL :



Modern AI (GPT-4, Claude, Gemini) is multimodal — it can see AND read AND hear!

# Visual Question Answering (VQA)

Image:

[Red car on  
a road with  
trees]

Requires BOTH:

- Understanding image
- Understanding language
- Reasoning about both!

Questions & Answers:

Q: "What color is the car?"

A: "Red"

Q: "Is it daytime or night?"

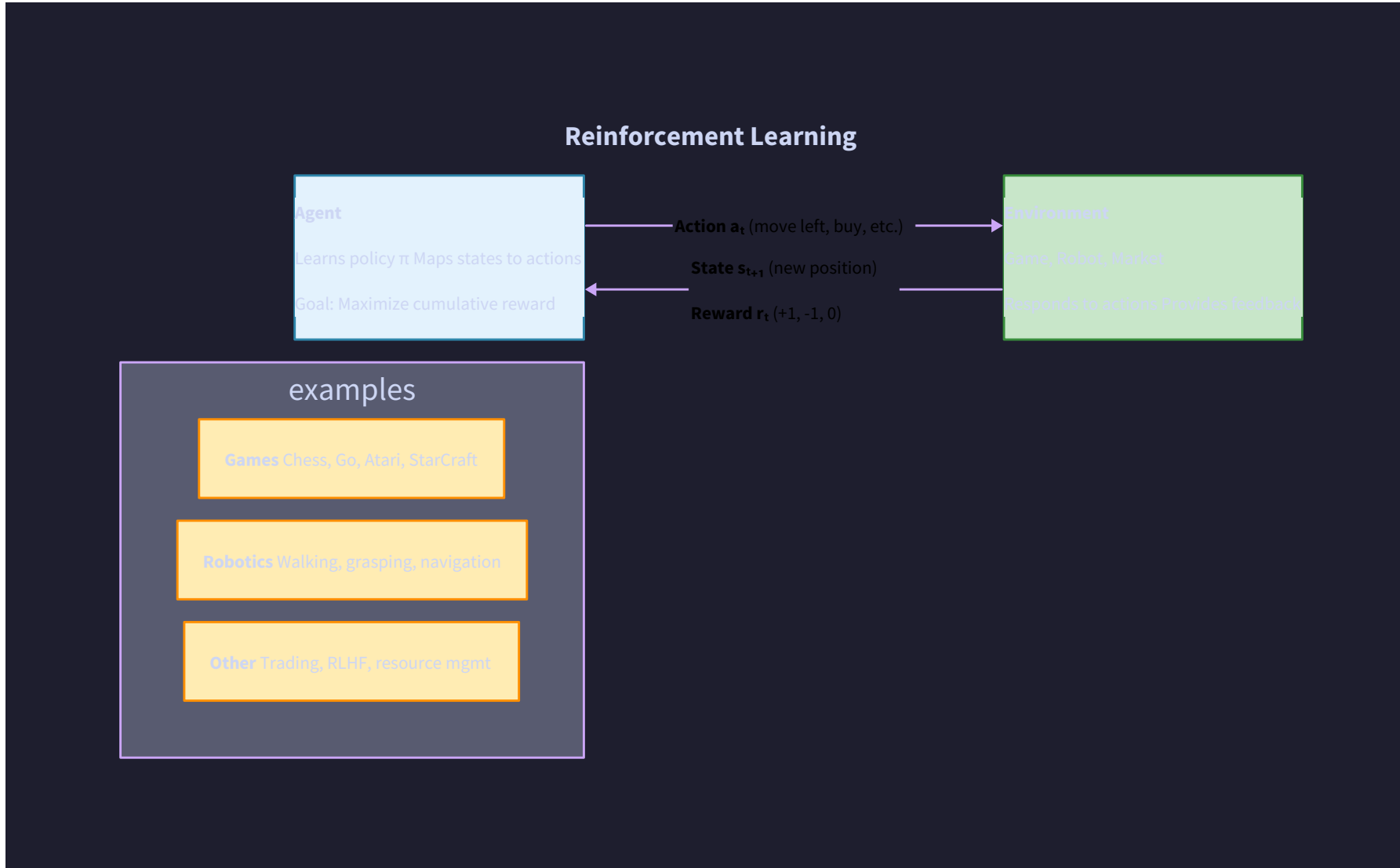
A: "Daytime"

Q: "How many trees are visible?"

A: "Four trees"

# Reinforcement Learning

A different paradigm: **Learning through interaction.**



# RL Examples

## GAME PLAYING

- AlphaGo: Beat world champion at Go
- AlphaStar: Grandmaster level at StarCraft II
- OpenAI Five: Beat pro teams at Dota 2

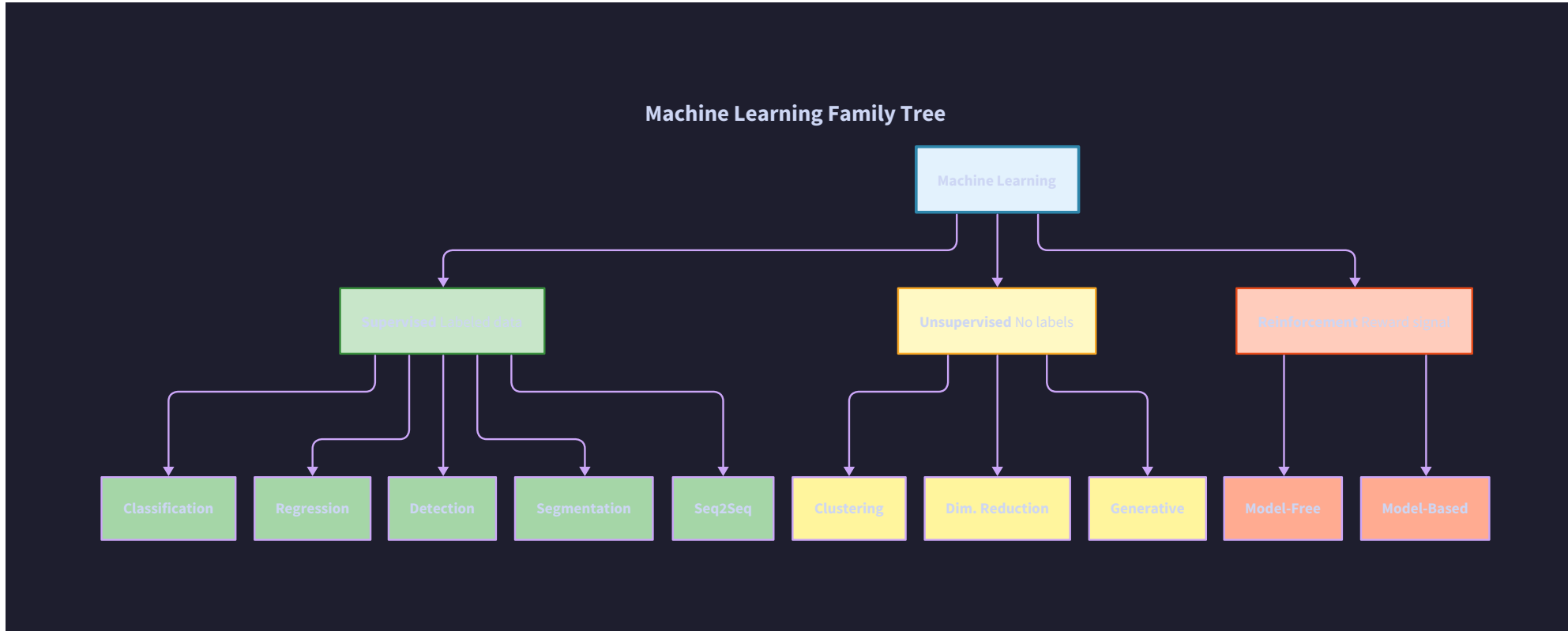
## ROBOTICS

- Boston Dynamics: Learning to walk, run, dance
- Robot arms: Learning to pick up objects
- Drones: Learning to navigate and avoid obstacles

## OTHER APPLICATIONS

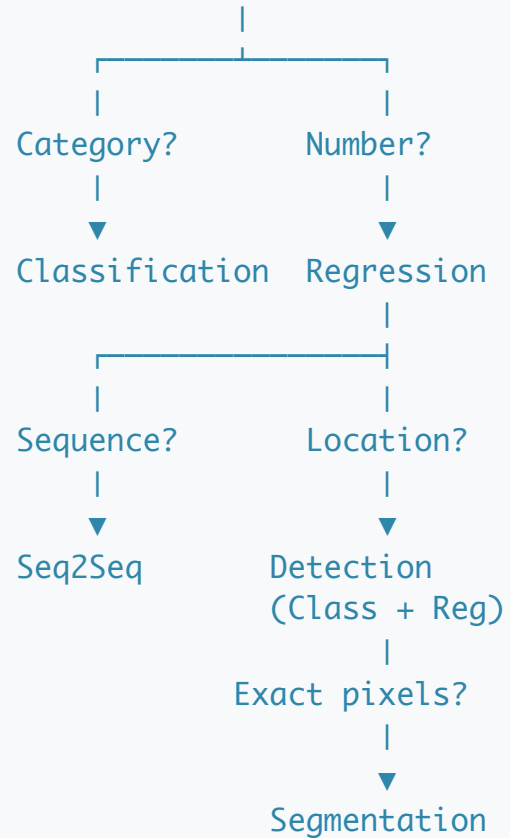
- Data center cooling (Google reduced energy 40%)
- Chip design (designing better AI chips!)
- Drug discovery (finding new molecules)
- RLHF: Making ChatGPT helpful and safe!

# Summary: The ML Family Tree



# The Decision Flowchart

START: What do you want to predict?



No labels available? → Unsupervised (Clustering, etc.)

Want to create new data? → Generative

Learning from trial/error? → Reinforcement Learning

# Key Takeaways

1. **Classification** → Predict a category (discrete)
2. **Regression** → Predict a number (continuous)
3. **Detection** → Classification + Box Regression
4. **Segmentation** → Classification for every pixel
5. **Seq2Seq** → Sequence in, sequence out (translation, etc.)
6. **Unsupervised** → Find patterns without labels
7. **Generative** → Create new data
8. **Multimodal** → Combine text, images, audio, etc.
9. **RL** → Learn from rewards through interaction

Understanding the output type tells you which family of techniques to use!



# What's Next?

In the **ML Tasks Zoo** lecture, we'll dive deeper into:

- 40+ specific tasks across all domains
- Computer Vision tasks in detail
- NLP tasks explained
- Audio processing
- And much more!

# Thank You!

**"All models are wrong, but some are useful."** — George Box

The key is matching the right model to the right task!

**Questions?**