The Machine Learning Task Zoo

A Safari Through 40+ Real-World AI Problems

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What We'll Explore Today

```
┌─────────────────────────────────────────────────────────────────────┐
│                    THE ML TASK SAFARI MAP                           │
├─────────────────────────────────────────────────────────────────────┤
│                                                                     │
│   COMPUTER VISION             NATURAL LANGUAGE PROCESSING           │
│   Classification              Sentiment Analysis                    │
│   Detection                   Named Entity Recognition              │
│   Segmentation               Translation                            │
│   Pose Estimation            Summarization                          │
│   Depth Estimation           Question Answering                     │
│                                                                     │
│   AUDIO & SPEECH              GENERATIVE MODELS                     │
│   Speech-to-Text             Image Generation                       │
│   Text-to-Speech             Text Generation                        │
│   Speaker Recognition        Video Generation                       │
│                                                                     │
│   REINFORCEMENT               MULTIMODAL                            │
│   Game Playing               Visual QA                              │
│   Robot Control              Image Captioning                       │
│                                                                     │
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```
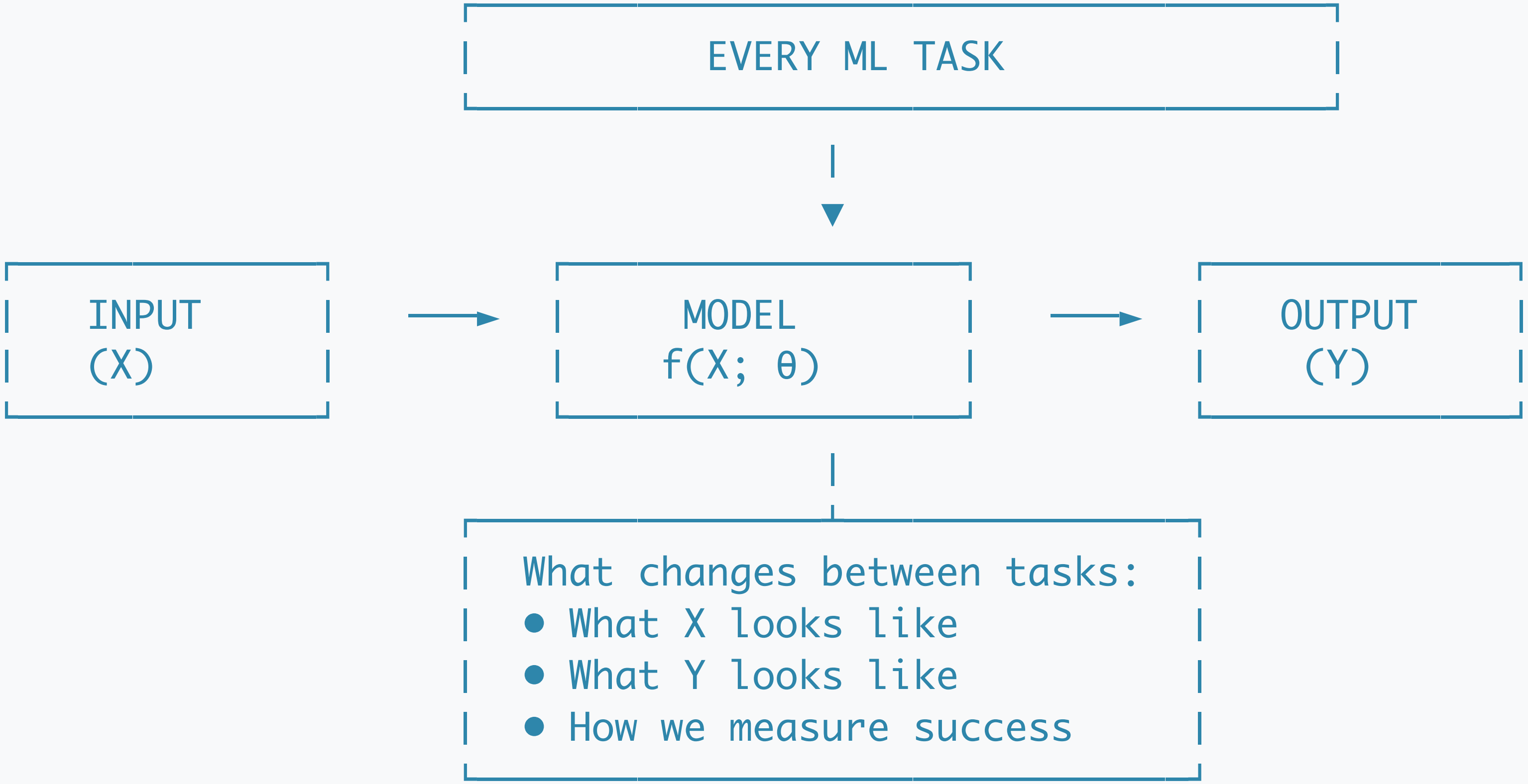

The Universal ML Recipe

Before we dive into 40+ tasks, remember this simple pattern:



EVERY ML TASK

INPUT (X)

MODEL $f(X; \theta)$

OUTPUT (Y)

What changes between tasks:

- What X looks like
- What Y looks like
- How we measure success

> The same Transformer architecture powers ChatGPT, DALL-E, and self-driving cars!

How to Think About ML Tasks

Every task is defined by **what goes in** and **what comes out**:

```
┌─────────────────────────────────────────────────────────────────┐
│                                                                 │
│   INPUT (X)             MODEL                 OUTPUT (Y)        │
│   ─────────      ─────────────────        ─────────────        │
│   Image           │               │       "Cat"                 │
│   Text       ───►│    f(x; θ)    │───►   0.87                  │
│   Audio           │               │       [x, y, w, h]          │
│   Numbers         └───────────────┘       "Bonjour"             │
│                                                                 │
└─────────────────────────────────────────────────────────────────┘
```

> The same model architecture can solve many different tasks — what changes is the data!

A Simple Classification

```
┌─────────────────────────────────────────────────────────────┐
│                    ML TASKS BY INPUT/OUTPUT                  │
├─────────────────────────────────────────────────────────────┤
│                                                              │
│  INPUT TYPE          →        OUTPUT TYPE                   │
│  ─────────────────────────────────────────                  │
│                                                              │
│  Image               →        Label          (Classification)  │
│  Image               →        Boxes          (Detection)       │
│  Image               →        Pixel Labels   (Segmentation)    │
│  Image               →        Text           (Captioning)      │
│  Text                →        Label          (Sentiment)       │
│  Text                →        Text           (Translation)     │
│  Audio               →        Text           (Speech-to-Text)  │
│  Text                →        Audio          (Text-to-Speech)  │
│  Numbers             →        Number         (Regression)      │
│  Numbers             →        Groups         (Clustering)      │
│  Noise               →        Image          (Generation)      │
│  Text                →        Image          (Text-to-Image)   │
│  Game State          →        Action         (RL)              │
│                                                              │
└─────────────────────────────────────────────────────────────┘
```

Domain 1: Computer Vision

Teaching Machines to See

"A picture is worth a thousand words... to a neural network, it's worth millions of numbers!"

The Vision Task Hierarchy

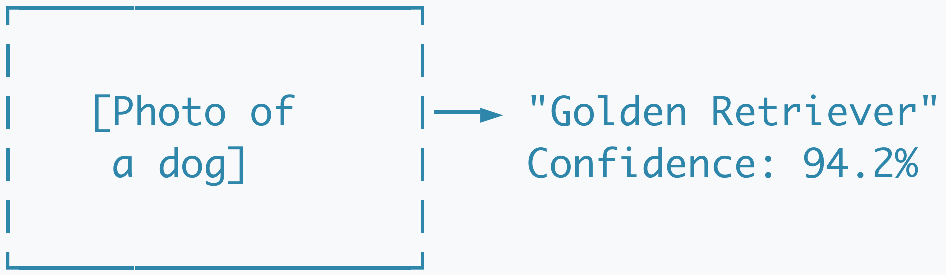
```
┌──────────────────────────────────────────────────────────────────────┐
│                                                                      │
│  LEVEL 1: Classification     "There's a dog somewhere in this image"  │
│  ────────────────────────────────────────────────────────────────    │
│         Easiest: Just need the answer                                │
│                                                                      │
│  LEVEL 2: Detection          "There's a dog at position (x, y, w, h)" │
│  ────────────────────────────────────────────────────────────────    │
│         Harder: Need to locate it with a box                         │
│                                                                      │
│  LEVEL 3: Segmentation       "These exact pixels belong to the dog"   │
│  ────────────────────────────────────────────────────────────────    │
│         Even harder: Pixel-perfect boundaries                        │
│                                                                      │
│  LEVEL 4: Pose Estimation    "Dog's head is at (x₁,y₁), legs at ..."  │
│  ────────────────────────────────────────────────────────────────    │
│         Hardest: Find specific body parts/keypoints                  │
│                                                                      │
└──────────────────────────────────────────────────────────────────────┘

                ▲
                |
         More precision, more data, more compute needed
```

Let's See This Visually

```
SAME IMAGE, DIFFERENT TASKS:

┌────────────────────────────────────────────────────────────────────────┐
│                                                                        │
│  CLASSIFICATION        DETECTION          SEGMENTATION    POSE         │
│  ───────────────       ─────────          ────────────    ────         │
│                                                                        │
│  ┌───────────┐        ┌───────────┐       ┌───────────┐   ┌───────┐    │
│  │           │        │  ┌─────┐  │       │  ▓▓▓▓▓    │   │    *  │    │
│  │  [Dog]    │        │  │ Dog │  │       │ ▓▓▓▓▓▓▓   │   │   /|\ │    │
│  │           │        │  │ 95% │  │       │▓▓▓▓▓▓▓▓▓  │   │   / \ │    │
│  │           │        │  └─────┘  │       │ ▓▓▓ ▓▓▓   │   │  *   *│    │
│  └───────────┘        └───────────┘       └───────────┘   └───────┘    │
│                                                                        │
│  Output: "Dog"       Output:             Output:         Output:       │
│                      [class, x,y,w,h]    Pixel mask      Keypoints     │
│                                                                        │
└────────────────────────────────────────────────────────────────────────┘
```

Task 1: Image Classification

What: Assign one label to an image.



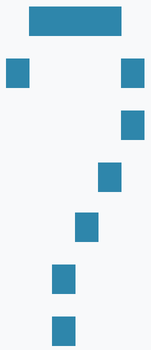
[Photo of a dog] → "Golden Retriever" Confidence: 94.2%

Real-world uses:

- Google Photos auto-tagging
- Medical X-ray diagnosis
- Quality control in factories
- Plant disease detection

Example: MNIST Digits

```
Input:  28×28 grayscale image
Output: One of {0, 1, 2, ..., 9}
```



→ "7" (98.5%)

10 classes, 60K training images

The "Hello World" of computer vision!

The Math Behind Classification

```
Input Image (e.g., 224 × 224 × 3 = 150,528 numbers)
                    │
                    ▼
           ┌───────────────────┐
           │   Neural Network    │
           │   (millions of      │
           │    parameters)      │
           └─────────┬─────────┘
                     │
                     ▼
           Raw scores (logits)
           [2.5, -1.2, 8.7, 0.3, ...]  (one per class)
                     │
                     ▼
           ┌───────────────────┐
           │     Softmax       │  ← Converts to probabilities
           └─────────┬─────────┘
                     │
                     ▼
           [0.01, 0.00, 0.94, 0.05, ...]  (sums to 1.0)
                     │
                     ▼
           Prediction: Class 3 (94% confidence)
```

ImageNet: The Olympics of Image Classification

```
┌─────────────────────────────────────────────────────────────────────┐
│                        IMAGENET CHALLENGE                           │
├─────────────────────────────────────────────────────────────────────┤
│                                                                     │
│   Dataset:  14 million images, 1000 classes                         │
│                                                                     │
│   Classes include:                                                  │
│   ┌─────────┐ ┌─────────┐ ┌─────────┐ ┌─────────┐ ┌─────────┐     │
│   │ [Dog]   │ │ [Car]   │ │ [Music] │ │ [Food]  │ │ [Home]  │     │
│   │ 120 dog │ │ Cars    │ │ Musical │ │ Foods   │ │ Objects │     │
│   │ breeds! │ │         │ │ instr.  │ │         │ │         │     │
│   └─────────┘ └─────────┘ └─────────┘ └─────────┘ └─────────┘     │
│                                                                     │
│   Year    Winner           Top-5 Error    Note                      │
│   ─────────────────────────────────────────────────                 │
│   2010    Traditional ML   28.2%          Hand-crafted features    │
│   2012    AlexNet (CNN)    16.4%          Deep learning begins!    │
│   2015    ResNet           3.6%           Superhuman performance!  │
│   2020    ViT              1.0%           Transformers enter vision│
│                                                                     │
└─────────────────────────────────────────────────────────────────────┘
```

Multi-Label Classification

Sometimes one label isn't enough!

```
┌──────────────────────────────────────────────────────────────────────┐
│                                                                      │
│   SINGLE-LABEL                    MULTI-LABEL                        │
│   ────────────                    ───────────                        │
│                                                                      │
│   ┌────────────┐                  ┌────────────┐                     │
│   │            │                  │            │                     │
│   │   [Cat]    │ -> "Cat"         │ Cat + Dog  │ -> ["Cat", "Dog"]  │
│   │            │   (one class)    │   + Couch  │    ["Couch"]        │
│   └────────────┘                  └────────────┘   ["Indoors"]       │
│                                                                      │
│   Each image has                  Each image can have                │
│   exactly ONE label               MULTIPLE labels                    │
│                                                                      │
│   Use: Softmax                    Use: Sigmoid (per class)           │
│   Σ probabilities = 1             Each class: 0 to 1 independently   │
│                                                                      │
└──────────────────────────────────────────────────────────────────────┘
```

> **Instagram uses multi-label classification** for their photo tags and content moderation!

Task 2: Object Detection

What: Find objects AND locate them with boxes.

```
┌──────────────────────────┐
│  ┌────┐                  │
│  │dog │   ┌──────┐       │
│  │0.95│   │person│       │
│  └────┘   │ 0.91 │       │
│           └──────┘       │
└──────────────────────────┘
```

Output for each detection:

- Class label ("dog")
- Confidence score (0.95)
- Bounding box: (x, y, width, height)

Example: Self-Driving Car

```
Detections in one frame:
├─ Car      at (120, 80)  conf: 0.97
├─ Car      at (400, 90)  conf: 0.89
├─ Person   at (300, 150) conf: 0.92
├─ Bicycle  at (50, 200)  conf: 0.88
└─ Traffic  at (250, 20)  conf: 0.99
   Light

Must process 30+ frames/second!
```

Detection vs Classification: Key Differences

```
┌─────────────────────────────────────────────────────────────────────┐
│                  CLASSIFICATION vs DETECTION                        │
├─────────────────────────────────────────────────────────────────────┤
│                                                                     │
│   CLASSIFICATION                  DETECTION                         │
│   ──────────────                  ─────────                         │
│                                                                     │
│   Input:  One image               Input:  One image                 │
│   Output: One label               Output: List of (class, box)      │
│                                                                     │
│   Assumes: Object fills           Handles: Multiple objects,        │
│            most of image                   any size, anywhere       │
│                                                                     │
│   Architecture:                   Architecture:                     │
│   CNN → FC → Softmax              CNN → Multiple detection heads    │
│                                                                     │
│   Example:                        Example:                          │
│   "Is this a cat or dog?"         "Find all cats and dogs"          │
│                                                                     │
│   Popular Models:                 Popular Models:                   │
│   ResNet, EfficientNet            YOLO, Faster R-CNN, DETR          │
│                                                                     │
└─────────────────────────────────────────────────────────────────────┘
```

How YOLO Works (Simplified)

"You Only Look Once" - Fast single-pass detection

```
┌──────────────────────────────────────────────────────────────────┐
│                                                                  │
│   Step 1: Divide image into grid (e.g., 7×7)                     │
│                                                                  │
│   ┌───┬───┬───┬───┬───┬───┬───┐                                  │
│   │   │   │   │   │   │   │   │                                  │
│   ├───┼───┼───┼───┼───┼───┼───┤    Each cell predicts:           │
│   │   │   │DOG│   │   │   │   │    * B bounding boxes            │
│   ├───┼───┼───┼───┼───┼───┼───┤    • Confidence scores           │
│   │   │   │   │   │   │   │   │    • C class probabilities       │
│   ├───┼───┼───┼───┼───┼───┼───┤                                  │
│   │   │   │   │   │   │CAT│   │                                  │
│   ├───┼───┼───┼───┼───┼───┼───┤                                  │
│   │   │   │   │   │   │   │   │                                  │
│   └───┴───┴───┴───┴───┴───┴───┘                                  │
│                                                                  │
│   Step 2: Remove overlapping boxes (Non-Max Suppression)         │
│   Step 3: Output final detections                                │
│                                                                  │
└──────────────────────────────────────────────────────────────────┘
```

Task 3: Semantic Segmentation

What: Label every pixel with its class.

```
ORIGINAL IMAGE:                       SEMANTIC SEGMENTATION:

┌──────────────────────┐              ┌───────────────────────┐
│ SSSSSSSSSSSSSSSSSSSS │              │ ░░░░░░░░░░░░░░░░░░░░  │  ░ = Sky
│ SSSSSSSSSSSSSSSSSSSS │              │ ░░░░░░░░░░░░░░░░░░░░  │
│                      │              │                       │
│  [Car1]    [Car2]    │     ───→     │  ▓▓▓▓▓    ▓▓▓▓▓      │  ▓ = Car
│                      │              │                       │
│ RRRRRRRRRRRRRRRRRRRR │              │ ████████████████████  │  █ = Road
│ RRRRRRRRRRRRRRRRRRRR │              │ ████████████████████  │
└──────────────────────┘              └───────────────────────┘


Output: An image of same size where each pixel is colored by class
```

Both cars have the same color — semantic segmentation doesn't distinguish between instances of the same class!

Task 4: Instance Segmentation

What: Label every pixel AND distinguish individual objects.

```
SEMANTIC SEGMENTATION:                 INSTANCE SEGMENTATION:

┌──────────────────────┐               ┌──────────────────────┐
│ ░░░░░░░░░░░░░░░░░░░░ │               │ ░░░░░░░░░░░░░░░░░░░░ │
│ ░░░░░░░░░░░░░░░░░░░░ │               │ ░░░░░░░░░░░░░░░░░░░░ │
│                      │               │                      │
│  ▓▓▓▓▓    ▓▓▓▓▓      │      vs      │ 111111   222222      │
│                      │               │                      │
│ ████████████████████ │               │ ████████████████████ │
│ ████████████████████ │               │ ████████████████████ │
└──────────────────────┘               └──────────────────────┘


 Both cars = same "Car" color           Car #1 = Blue, Car #2 = Green
 Can't tell them apart!                 Can track each car individually
```

> **Self-driving cars need instance segmentation** — you must track which car is which to predict their movements!

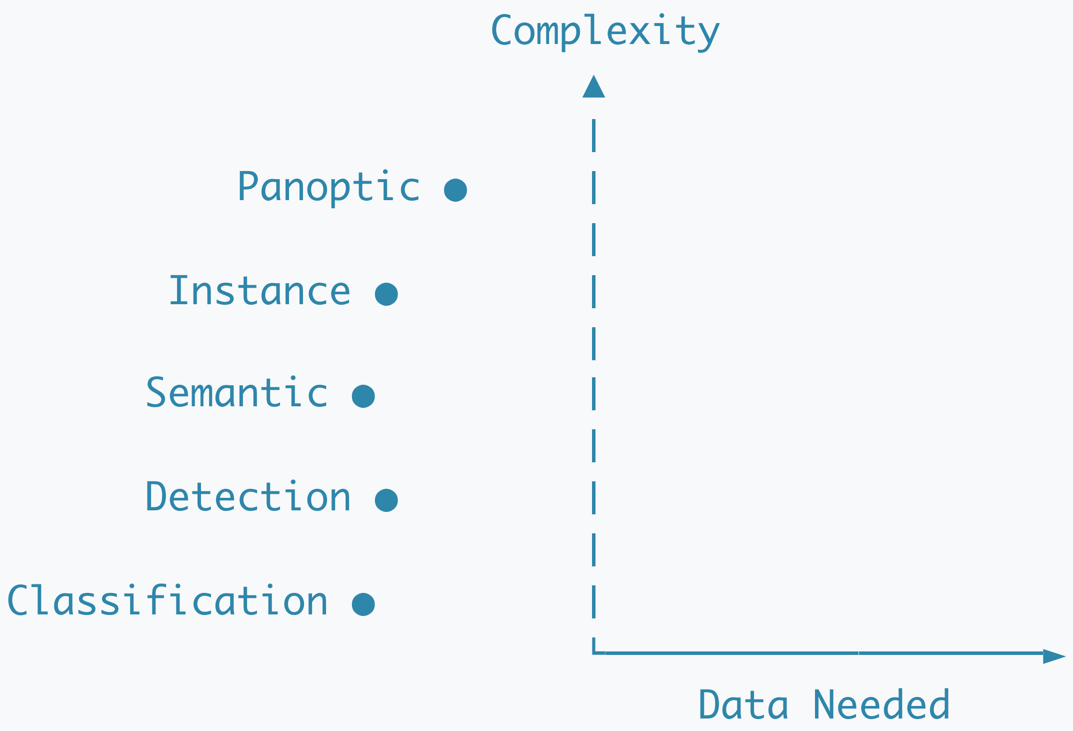
Panoptic Segmentation: The Complete Picture

Combining everything: Semantic + Instance

```
┌──────────────────────────────────────────────────────────────────────┐
│                                                                      │
│                      PANOPTIC SEGMENTATION                           │
│                                                                      │
│   ┌────────────────────────────────────────────────────────────┐     │
│   │ Sky (stuff - no instances)                                  │     │
│   │ ░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░░ │     │
│   │                                                            │     │
│   │    Car #1        Person #1        Car #2                   │     │
│   │    Car #1         Person #1        Car #2                 │     │
│   │                                                            │     │
│   │ Road (stuff - no instances)                                │     │
│   │ ████████████████████████████████████████████████████████ │     │
│   └────────────────────────────────────────────────────────────┘     │
│                                                                      │
│   "Stuff" classes: sky, road, grass (don't count instances)          │
│   "Things" classes: cars, people (each instance gets unique ID)      │
│                                                                      │
└──────────────────────────────────────────────────────────────────────┘
```

Segmentation Summary

Task	What it outputs	Can count objects?	Use case
Semantic	Pixel classes	No	Land use mapping, medical imaging
Instance	Pixel + instance IDs	Yes	Object tracking, robotics
Panoptic	Both combined	Yes for "things"	Autonomous driving



Task 5: Pose Estimation

What: Find body keypoints (skeleton) of humans or animals.

```
Original Photo:                    Detected Skeleton:

  ┌──────────────┐                       ●  ← Head (nose, eyes, ears)
  │              │                      /|\
  │    Person    │        ──►          / | \
  │   standing   │                    ●  ●  ●  ← Shoulders
  │     with     │                       |
  │  raised arm  │                      / \
  └──────────────┘                     ●   ●  ← Hips
                                      /     \
                                     ●       ●  ← Knees
                                    /         \
                                   ●           ●  ← Ankles

Output: 17 keypoints with (x, y, confidence) each
```

Pose Estimation: Real Applications

Fitness & Sports

```
┌─────────────────────┐
│    Squat Form       │
│    Analysis         │
│         ●           │
│        /|\          │
│       / | \         │
│         |           │
│        / \          │
│       ●   ●         │
│      ↑     ↑        │
│   "Knees too far    │
│    over toes!"      │
└─────────────────────┘
```

Other Applications

- Motion capture for movies/games
- Running form analysis
- Dance move recognition
- Sign language interpretation
- Controller-free gaming (Kinect)
- Fall detection for elderly

> **Apple Fitness+** uses pose estimation to analyze your workout form in real-time!

Task 6: Depth Estimation

What: Predict distance of each pixel from the camera.

```
RGB Image:                          Depth Map:
┌──────────────────────┐            ┌──────────────────────┐
│                      │            │ ░░░░░░░░░░░░░░░░░░░░ │  ░ = Far
│    Mountains         │            │ ░░░░░░░░░░░░░░░░░░░░ │      (light)
│                      │            │                      │
│    Trees             │    -->     │  ▓▓▓▓▓              │ ▓ = Medium
│                      │            │                      │
│    Car (close)       │            │ ████████████         │  █ = Close
│                      │            │                      │      (dark)
└──────────────────────┘            └──────────────────────┘

Output: Same-size image where pixel intensity = distance
```

One camera, 3D understanding! Traditional 3D sensing requires special hardware (LiDAR, stereo cameras), but AI can estimate depth from a single RGB image.

Depth Estimation: How It's Used

AR/VR

```
Place virtual
furniture in
your room!

   [Sofa]
   (knows it's
   on the floor)
```

Portrait Mode

```
Blur background
based on depth

  [Person sharp]
  ░░░ (blurred)
```

Robotics

```
Navigate without
bumping into
objects

  Robot --> Box
  (knows distance)
```

The iPhone's Portrait Mode uses a combination of depth sensors AND neural network depth estimation!

Task 7: Optical Flow

What: Track how each pixel moves between video frames.

```
Frame t:                Frame t+1:              Flow Vectors:
┌───────────────┐       ┌───────────────┐       ┌───────────────┐
│               │       │               │       │               │
│   ●           │  ──►  │          ●    │   =   │   ────────►   │
│   (ball)      │       │   (ball)      │       │               │
│               │       │               │       │               │
│       ▲       │       │     ▲         │       │        ◄──    │
│     (person)  │       │ (person)      │       │               │
└───────────────┘       └───────────────┘       └───────────────┘

                                                Each pixel gets
                                                a motion vector
```

Key insight: Every pixel gets a (dx, dy) vector showing where it moved!

Optical Flow Applications

```
┌──────────────────────────────────────────────────────────────────────┐
│                      OPTICAL FLOW USE CASES                          │
├──────────────────────────────────────────────────────────────────────┤
│                                                                      │
│  VIDEO COMPRESSION                                                   │
│  Instead of storing every frame, store keyframes + motion vectors   │
│  Result: 10x smaller file sizes                                     │
│                                                                      │
│  ACTION RECOGNITION                                                  │
│  "Running" = specific pattern of flow vectors                       │
│  "Waving" = different pattern                                       │
│                                                                      │
│  AUTONOMOUS DRIVING                                                  │
│  Objects moving towards you → collision warning                     │
│  Everything moving left → you're turning right                      │
│                                                                      │
│  VIDEO GAMES                                                         │
│  Frame interpolation: turn 30fps into 60fps                         │
│                                                                      │
└──────────────────────────────────────────────────────────────────────┘
```

Task 8: Face Recognition

What: Identify WHO a face belongs to.

```
┌────────────────┐      ┌────────────────────────────────────────────┐
│                │      │                                            │
│     [Face      │ ───► │   Face Embedding: [0.23, -0.41, 0.87, ...│
│      Image]    │      │   (128-dimensional vector)                 │
│                │      │                                            │
└────────────────┘      └────────────────────────────────────────────┘
                                         │
                                         ▼
                         ┌────────────────────────────────┐
                         │  Compare with database         │
                         │                                │
                         │  Distance to "Nipun": 0.15   │ ← Match!
                         │  Distance to "Alice": 0.89   │
                         │  Distance to "Bob":   0.92   │
                         └────────────────────────────────┘
                                         │
                                         ▼
                              "Match: Nipun Batra"
```

Face Detection ≠ Face Recognition

```
┌─────────────────────────────────────────────────────────────────────┐
│                                                                     │
│   FACE DETECTION                    FACE RECOGNITION                │
│   ──────────────                    ────────────────                │
│                                                                     │
│   Question: "Where are              Question: "Who is               │
│              the faces?"                       this person?"        │
│                                                                     │
│   ┌───────────────────┐            ┌───────────────────┐            │
│   │  ┌───┐            │            │      ┌───┐        │            │
│   │  │ ? │   ┌───┐    │            │      │ ID │        │            │
│   │  └───┘   │ ? │    │            │      └───┘        │            │
│   │          └───┘    │            │        ↓          │            │
│   └───────────────────┘            │   "This is Nipun" │            │
│                                    └───────────────────┘            │
│   Output: Bounding boxes           Output: Identity label           │
│                                                                     │
│   Used BEFORE recognition          Requires database of             │
│   (find faces first)               known faces                      │
│                                                                     │
└─────────────────────────────────────────────────────────────────────┘
```

Vision Tasks Summary

Task	Input	Output	Example Use
Classification	Image	Label	"Is this spam?"
Detection	Image	Boxes + labels	Self-driving cars
Segmentation	Image	Pixel mask	Medical imaging
Pose Estimation	Image	Keypoints	Fitness apps
Depth Estimation	Image	Depth map	AR furniture
Optical Flow	2 frames	Motion vectors	Video compression
Face Recognition	Face	Identity	Phone unlock

Domain 2: Natural Language Processing

Teaching Machines to Read & Write

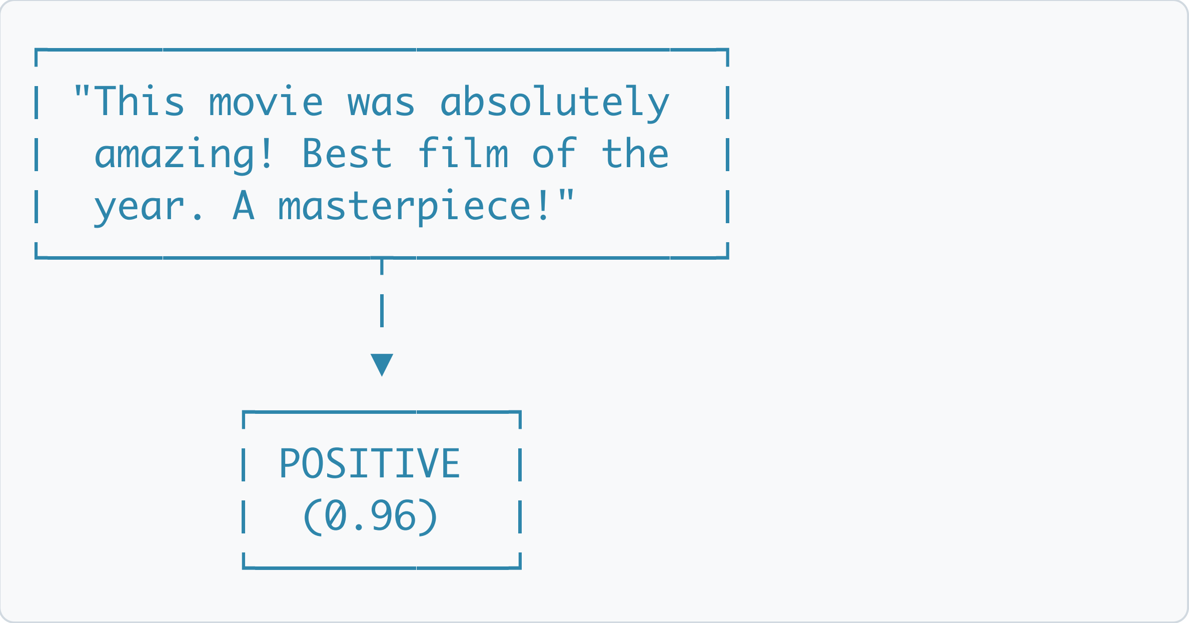
"Language is the dress of thought." — Samuel Johnson

The NLP Task Landscape

```
┌──────────────────────────────────────────────────────────────────────┐
│                         NLP TASKS                                      │
├──────────────────────────────────────────────────────────────────────┤
│                                                                        │
│   UNDERSTANDING TASKS              GENERATION TASKS                    │
│   ──────────────────               ────────────────                    │
│                                                                        │
│   • Sentiment Analysis             • Text Generation                   │
│     (Is this positive?)              (Write like Shakespeare)         │
│                                                                        │
│   • Named Entity Recognition       • Summarization                     │
│     (Find names, places, dates)      (Shorten this article)           │
│                                                                        │
│   • Question Answering             • Translation                       │
│     (Find the answer)                (English → Hindi)                │
│                                                                        │
│   • Topic Classification           • Paraphrasing                      │
│     (Sports? Politics? Tech?)        (Same meaning, new words)        │
│                                                                        │
│   ─────────────────────────────────────────────────────────────      │
│                                                                        │
│   MODERN LLMS CAN DO ALL OF THESE WITH A SINGLE MODEL!               │
│                                                                        │
└──────────────────────────────────────────────────────────────────────┘
```

Task 9: Sentiment Analysis

What: Classify text by emotion/opinion.



"This movie was absolutely amazing! Best film of the year. A masterpiece!"

POSITIVE (0.96)

Output Options:

Binary:	Positive / Negative
3-class:	Positive / Neutral / Negative
5-class:	1 to 5 stars
Continuous:	-1.0 to +1.0 (very negative → very positive)

Sentiment Analysis: Real World

Brand Monitoring

```
Twitter Stream:
+- "Love the new iPhone!" -> Positive
+- "Battery dies so fast" -> Negative
+- "Just bought one!"     -> Neutral
+- "Worst purchase ever"  -> Negative
+- "Camera is incredible" -> Positive

Daily Sentiment: 67% positive
```

Customer Feedback

```
Support Tickets:

┌─────────────────────────┐
| Urgent (Negative) ●●●●  |
| Normal  (Neutral) ●●    |
| Praise  (Positive) ●    |
└─────────────────────────┘

→ Route angry customers
  to senior support!
```

> **Amazon analyzes millions of reviews** using sentiment analysis to understand product reception!

The Challenge: Sarcasm & Context

```
┌─────────────────────────────────────────────────────────────────────┐
│                      WHY SENTIMENT IS HARD                           │
├─────────────────────────────────────────────────────────────────────┤
│                                                                      │
│  SARCASM:                                                            │
│  "Oh great, another software update. Just what I needed."            │
│   Words: positive ("great", "needed")                                │
│   Meaning: NEGATIVE                                                  │
│                                                                      │
│  NEGATION:                                                           │
│  "This movie is not bad."                                            │
│   Contains "bad" → but overall POSITIVE                              │
│                                                                      │
│  CONTEXT:                                                            │
│  "The battery lasts forever" (phone review) → POSITIVE               │
│  "This movie lasts forever" (movie review) → NEGATIVE                │
│                                                                      │
│  MIXED:                                                              │
│  "The food was great but the service was terrible."                  │
│   Overall? Positive? Negative? Neutral? Depends on priority!         │
│                                                                      │
└─────────────────────────────────────────────────────────────────────┘
```

Task 10: Named Entity Recognition (NER)

What: Find and label names, places, dates, organizations, etc.

```
Input:  "Elon Musk announced that Tesla will open a factory
         in Berlin by March 2025."

        ┌────────┐                    ┌───────┐
        │ PERSON │                    │  ORG  │
        └───┬────┘                    └───┬───┘
            │                             │
            ▼                             ▼
Output: "Elon Musk announced that Tesla will open a factory

                                        ┌───────┐ ┌──────────┐
                                        │  LOC  │ │   DATE   │
                                        └───┬───┘ └────┬─────┘
                                            │          │
                                            ▼          ▼
         in Berlin by March 2025."
```

NER: Entity Types

```
┌─────────────────────────────────────────────────────────────────────┐
│                    COMMON NER ENTITY TYPES                          │
├─────────────────────────────────────────────────────────────────────┤
│                                                                     │
│   TYPE          EXAMPLES                      COLOR CODE            │
│   ─────         ─────────                     ──────────            │
│   PERSON        Elon Musk, Marie Curie        [Blue]                │
│   ORGANIZATION  Tesla, Google, UN             [Green]               │
│   LOCATION      Berlin, Mount Everest         [Yellow]              │
│   DATE          March 2025, last Tuesday      [Orange]              │
│   MONEY         $5 million, €100              [Brown]               │
│   PERCENT       15%, three percent            [White]               │
│   TIME          3:30 PM, midnight             [Purple]              │
│   PRODUCT       iPhone 15, Model S            [Red]                 │
│                                                                     │
│   Domain-specific:                                                  │
│   - Medical: DISEASE, DRUG, SYMPTOM                                 │
│   - Legal: CASE_NUMBER, COURT, JUDGE                                │
│   - Finance: TICKER, EXCHANGE, CURRENCY                             │
│                                                                     │
└─────────────────────────────────────────────────────────────────────┘
```

NER: Real Applications

Search Engines

```
Query: "restaurants near
        Eiffel Tower"

NER finds:
└─ LOCATION: "Eiffel Tower"

→ Shows map of Paris
→ Lists nearby restaurants
```

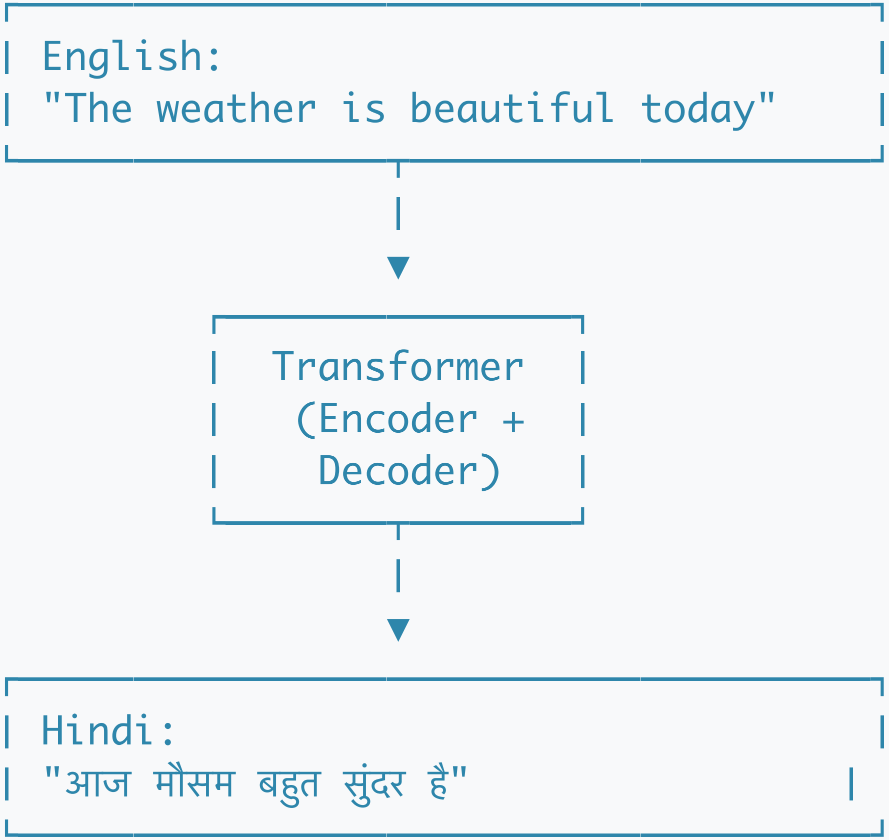
Knowledge Graphs

```
Text: "Tim Cook is the
       CEO of Apple"

Extracted:
┌──────────┐    ┌────────┐
│Tim Cook  │───►│ Apple  │
└──────────┘CEO └────────┘
   PERSON     of    ORG
```

> **Google Search** uses NER to understand your queries and build its Knowledge Graph!

Task 11: Machine Translation

What: Convert text from one language to another.



```
┌──────────────────────────────────┐
│ English:                         │
│ "The weather is beautiful today" │
└──────────────────────────────────┘
                │
                │
                ▼
        ┌──────────────┐
        │  Transformer │
        │  (Encoder +  │
        │   Decoder)   │
        └──────────────┘
                │
                │
                ▼
┌──────────────────────────────────┐
│ Hindi:                           │
│ "आज मौसम बहुत सुंदर है"          │
└──────────────────────────────────┘
```

Translation Challenges

```
┌──────────────────────────────────────────────────────────────────────┐
│                    WHY TRANSLATION IS HARD                            │
├──────────────────────────────────────────────────────────────────────┤
│                                                                       │
│  WORD ORDER:                                                          │
│  English: "I eat an apple"     (Subject-Verb-Object)                  │
│  Japanese: " はりんごを べる"   (Subject-Object-Verb)                   │
│                                                                       │
│  IDIOMS:                                                              │
│  "It's raining cats and dogs" → Not about animals!                    │
│  Must translate the MEANING, not words                                │
│                                                                       │
│  CONTEXT:                                                             │
│  "The bank is by the river"                                           │
│  - bank = financial institution? river bank?                          │
│                                                                       │
│  CULTURAL CONCEPTS:                                                   │
│  Some words have no direct translation                                │
│  - Japanese "  れ  " (komorebi): sunlight filtering through trees      │
│                                                                       │
│  GENDER/FORMALITY:                                                    │
│  "You" in English = tu/vous in French (formal vs informal)            │
│                                                                       │
└──────────────────────────────────────────────────────────────────────┘
```

Task 12: Text Summarization

Extractive: Pick important sentences verbatim.

```
Long Article:
┌─────────────────────┐
| Sentence 1          | ← Keep
| Sentence 2          |
| Sentence 3          |
| Sentence 4          | ← Keep
| Sentence 5          |
| Sentence 6          | ← Keep
| ...                 |
└─────────────────────┘

Just highlights!
No new words created.
```

Abstractive: Generate new text (paraphrase).

```
Long Article:
┌─────────────────────┐
| [Original 1000      |
|  words about        |
|  climate change...] |
└──────────┬──────────┘
           | AI rewrites
           ▼
┌─────────────────────┐
| "Climate scientists |
|  warn that global   |
|  temperatures..."   |
|  (100 words)        |
└─────────────────────┘
```

LLMs like GPT-4 and Claude do **abstractive** summarization — they truly understand and paraphrase!

Task 13: Question Answering

Extractive QA:

Find answer span in given text.

```
Context: "Albert Einstein
was born in Ulm, Germany
on March 14, 1879."

Question: "Where was
Einstein born?"

Answer: "Ulm, Germany"
        ▲
        └── Highlighted from
            the context text
```

Generative QA:

Generate free-form answer.

```
Question: "Explain
quantum entanglement
to a 5-year-old."

Answer: "Imagine you have
two magic coins. When
you flip one and it
lands on heads, the
other one ALWAYS lands
on heads too, even if
it's on the moon!"
        ▲
        └── Created new text
            (not from any doc)
```

QA: The Evolution

```
┌─────────────────────────────────────────────────────────────────────┐
│                   QUESTION ANSWERING EVOLUTION                      │
├─────────────────────────────────────────────────────────────────────┤
│                                                                     │
│   ERA 1: Rule-Based (1960s-2000s)                                   │
│   ─────────────────────────────────                                 │
│   Keywords → Database lookup → Template answer                      │
│   "Very brittle, only worked for specific domains"                  │
│                                                                     │
│   ERA 2: Extractive (2016-2020)                                     │
│   ───────────────────────────────                                   │
│   BERT-style: "Find the answer IN the text"                         │
│   Great for reading comprehension tasks                             │
│                                                                     │
│   ERA 3: Generative (2020-present)                                  │
│   ──────────────────────────────────                                │
│   LLMs: Generate answers from learned knowledge                     │
│   Can answer questions about ANYTHING                               │
│   Can reason, explain, and elaborate                                │
│                                                                     │
│   ERA 4: RAG (Retrieval-Augmented Generation)                       │
│   ─────────────────────────────────────────────                     │
│   LLM + Search = Best of both worlds                                │
│   Accurate, up-to-date, with sources                                │
│                                                                     │
└─────────────────────────────────────────────────────────────────────┘
```

Task 14: Text Generation (LLMs)

What: Predict and generate the next tokens, one at a time.

```
Prompt:  "The secret to happiness is"
           │
           ▼
    ┌─────────────────┐
    │      LLM        │
    │  (GPT, Claude,  │
    │   Gemini, etc.) │
    └────────┬────────┘
             │
             ▼
Token 1: "not"     P("not" | prompt) = 0.15
             │
             ▼
Token 2: "in"      P("in" | prompt + "not") = 0.42
             │
             ▼
Token 3: "wealth"  P("wealth" | ... + "in") = 0.23
             │
             ▼
         ... continues until <END> token

Output: "The secret to happiness is not in wealth but in
         meaningful connections with others."
```

How LLMs Generate Text

```
┌──────────────────────────────────────────────────────────────────────┐
│                    AUTOREGRESSIVE GENERATION                         │
├──────────────────────────────────────────────────────────────────────┤
│                                                                      │
│   Step 1: "The"        → predict next → "secret"                     │
│   Step 2: "The secret" → predict next → "to"                         │
│   Step 3: "The secret to" → predict next → "happiness"               │
│   ...                                                                │
│                                                                      │
│   Each step:                                                         │
│   ┌──────────────────────────────────────────────────────┐           │
│   │  Probability Distribution Over Vocabulary            │           │
│   │                                                       │          │
│   │  P("the")       = 0.02  ░                            │           │
│   │  P("happiness")= 0.25  ████████                      │           │
│   │  P("success")   = 0.18  ██████                       │           │
│   │  P("life")      = 0.12  ████                         │           │
│   │  P("love")      = 0.08  ███                          │           │
│   │  ...            = ...                                 │          │
│   └──────────────────────────────────────────────────────┘           │
│                                                                      │
│   Sample from this distribution (or take argmax)                     │
│                                                                      │
└──────────────────────────────────────────────────────────────────────┘
```

NLP Tasks Summary

Task	Input	Output	Key Challenge
Sentiment	Text	Positive/Negative	Sarcasm, context
NER	Text	Entity spans + types	Ambiguous names
Translation	Text (lang A)	Text (lang B)	Word order, idioms
Summarization	Long text	Short text	Keeping key info
QA	Question + context	Answer	Finding relevant info
Generation	Prompt	Continued text	Coherence, factuality

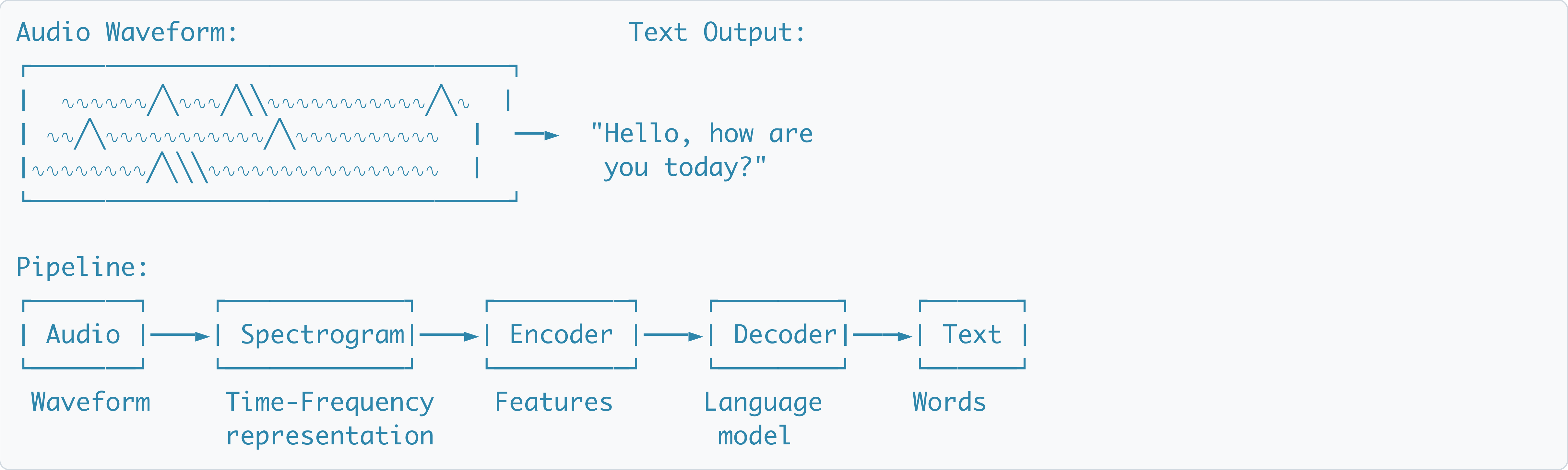
Domain 3: Audio & Speech

Teaching Machines to Hear

"The human voice is the most beautiful instrument of all." — Arvo Pärt

Task 15: Speech-to-Text (ASR)

What: Convert spoken audio to text.



Audio Waveform:

Text Output:

"Hello, how are you today?"

Pipeline:

ASR: The Spectrogram

Converting sound to "images" that neural networks can process

```
Audio Wave:                              Spectrogram:
                                         (time → frequency "image")
  ↑
Amplitude                                Frequency
  │     /\    /\    /\                        ↑
  │    /  \  /  \  /  \      ───────►   High  │ ░░░░░░░░░░
  │   /    \/    \/    \                      │ ░░░░░░░░░░
  │  /                  \                     │ ████░░░░░░
  └──────────────────────► Time          Low  │ ░░████░░██
                                              └──────────►
                                                   Time

Bright areas = loud frequencies at that moment
Pattern = unique "fingerprint" of each word!
```

Whisper by OpenAI can transcribe audio in 99 languages with near-human accuracy!

Task 16: Text-to-Speech (TTS)

What: Convert text to natural-sounding audio.

```
Text Input:                             Audio Output:
┌──────────────────────┐
│ "Welcome to the      │                ┌────────────────────┐
│  future of AI.       │      ──►       │  ∿∿∿/\∿∿∿/\\∿∿∿∿∿∿  │
│  This is exciting!"  │                │ ∿/\∿∿∿∿∿∿∿∿/\∿∿∿∿∿  │
└──────────────────────┘                └────────────────────┘

Modern TTS Pipeline:
┌──────┐    ┌─────────────┐    ┌──────────────┐    ┌───────────┐
│ Text │───►│ Text        │───►│ Acoustic     │───►│ Vocoder   │───► Audio
└──────┘    │ Analysis    │    │ Model        │    │ (Neural)  │
            └─────────────┘    └──────────────┘    └───────────┘
            (pronunciation,    (generates          (converts to
             emphasis)         mel-spectrogram)     waveform)
```

TTS: Then vs Now

```
┌──────────────────────────────────────────────────────────────────────┐
│                    TTS EVOLUTION                                     │
├──────────────────────────────────────────────────────────────────────┤
│                                                                      │
│   1990s: Concatenative TTS                                           │
│   ─────────────────────────                                          │
│   Splice together recorded phonemes                                  │
│   Result: Robotic, unnatural "The-wea-ther-to-day-is..."             │
│                                                                      │
│   2010s: Statistical Parametric TTS                                  │
│   ────────────────────────────────                                   │
│   HMM-based models, smoother but still artificial                    │
│                                                                      │
│   2016: WaveNet (DeepMind)                                           │
│   ─────────────────────────                                          │
│   Neural network generates audio sample by sample                    │
│   Human-like quality, but VERY slow                                  │
│                                                                      │
│   2020s: Parallel Neural TTS                                         │
│   ──────────────────────────                                         │
│   Real-time, expressive, can clone voices                            │
│   Examples: ElevenLabs, Bark, XTTS                                   │
│                                                                      │
└──────────────────────────────────────────────────────────────────────┘
```

Task 17-18: Speaker Recognition

Speaker Identification:

Who is speaking? (1-of-N)

```
Voice Sample
     │
     ▼
┌──────────────────┐
│  Voice Encoder   │
│  → Embedding     │
└────────┬─────────┘
         │
         ▼
   Compare to database
   of N known speakers
         │
         ▼
   "Speaker: Alice"
```

Speaker Verification:

Is this who they claim to be?

```
Voice + "I am Alice"
     │
     ▼
┌──────────────────┐
│  Voice Encoder   │
│  → Embedding     │
└────────┬─────────┘
         │
         ▼
   Compare to Alice's
   stored voiceprint
         │
         ▼
   ✅ Verified  or  ❌ Rejected
```

"Hey Siri" uses **speaker verification** — it only responds to the device owner's voice!

Domain 4: Unsupervised Learning

Finding Patterns Without Labels

"The goal is to find structure in chaos."

Task 19: Clustering

What: Group similar items together automatically (no labels needed!).

```
Before (unlabeled data):            After (3 clusters found):

    ●    ■                              ○    □          ○ = Cluster 1
  ●   ●    ■ ■                        ○   ○    □ □      □ = Cluster 2
    ●        ■                          ○        □      △ = Cluster 3


        ▲   ▲                              △   △
    ▲          ▲                       △          △
      ▲    ▲                             △    △

Algorithm (K-Means) figures out:
- There are 3 natural groups
- Which points belong to which group
```

Clustering: The K-Means Algorithm

```
┌─────────────────────────────────────────────────────────────────────┐
│                    K-MEANS: STEP BY STEP                            │
├─────────────────────────────────────────────────────────────────────┤
│                                                                     │
│  Step 1: Pick K random "centroids" (cluster centers)                │
│          ★                   ★                                      │
│                      ★                                              │
│                                                                     │
│  Step 2: Assign each point to nearest centroid                      │
│          ○○○ near ★1    □□□ near ★2    △△△ near ★3                  │
│                                                                     │
│  Step 3: Move centroids to center of their points                   │
│          ★1 moves to average of ○○○                                 │
│          ★2 moves to average of □□□                                 │
│          ★3 moves to average of △△△                                 │
│                                                                     │
│  Step 4: Repeat steps 2-3 until centroids stop moving               │
│                                                                     │
│  Done! Points are now clustered.                                    │
│                                                                     │
└─────────────────────────────────────────────────────────────────────┘
```

Clustering: Real Applications

Customer Segmentation

```
Cluster 1: "VIPs"
├─ High spending
├─ Infrequent visits
└─ Premium products

Cluster 2: "Regulars"
├─ Medium spending
├─ Weekly visits
└─ Staple items

Cluster 3: "Bargain Hunters"
├─ Low spending
├─ Sale days only
└─ Discounted items
```

Image Compression

```
Original: 16 million colors

After K-Means (K=16):
Only 16 colors!

┌────────────────────┐
| [Color Palette] |
| and 8 more shades |
└────────────────────┘

File size: 10x smaller
Quality: Still looks good!
```

Task 20: Anomaly Detection

What: Find the outliers / unusual patterns.

```
Normal Transactions:                   Anomaly Alert!
┌─────────────────────────────────────────────────────────────┐
│                                                             │
│   $50  $120  $45  $200  $75  $90  $15,000  $80  $110      │
│    ●     ●    ●     ●    ●    ●      ★      ●     ●       │
│                                      ▲                      │
│                                      |                      │
│                               ** FRAUD ALERT! **            │
│                               Unusual transaction           │
│                               detected!                     │
└─────────────────────────────────────────────────────────────┘
```

> Anomaly detection is "learning what's normal, then flagging what's not."

Anomaly Detection: Methods

```
┌──────────────────────────────────────────────────────────────────────┐
│                    ANOMALY DETECTION APPROACHES                      │
├──────────────────────────────────────────────────────────────────────┤
│                                                                      │
│  1. STATISTICAL                                                      │
│     If value is > 3 standard deviations from mean → Anomaly          │
│     Simple but assumes normal distribution                           │
│                                                                      │
│  2. DISTANCE-BASED                                                   │
│     If point is far from all other points → Anomaly                  │
│     Works for any shape of data                                      │
│                                                                      │
│  3. DENSITY-BASED                                                    │
│     If point is in a low-density region → Anomaly                    │
│     Good for varying cluster sizes                                   │
│                                                                      │
│  4. AUTOENCODER (Neural Network)                                     │
│     Train to reconstruct normal data                                 │
│     High reconstruction error → Anomaly                              │
│     Best for complex, high-dimensional data                          │
│                                                                      │
└──────────────────────────────────────────────────────────────────────┘
```

Task 21: Dimensionality Reduction

What: Compress high-dimensional data while preserving structure.

```
Original: 784 dimensions (28×28 MNIST image)

    ┌──────────────────────────────────────────┐
    │ [0.12, 0.45, 0.00, 0.87, 0.33, ....      │
    │  0.23, 0.00, 0.91, 0.14, .... (784)]     │
    └──────────────────────────────────────────┘
                         │
                         │  PCA / t-SNE / UMAP
                         ▼
    ┌──────────────────────────────────────────┐
    │             [0.45, -0.23]                │  ← Just 2D!
    └──────────────────────────────────────────┘
                         │
                         ▼
              Now we can visualize it!

        ●● ●●                   ← Cluster of "0"s
       ●●  ●●
         ▲▲ ▲▲▲                 ← Cluster of "1"s
           ▬▬ ▬▬                ← Cluster of "7"s
```

Why Reduce Dimensions?

```
┌────────────────────────────────────────────────────────────────────┐
│                    BENEFITS OF DIMENSIONALITY REDUCTION            │
├────────────────────────────────────────────────────────────────────┤
│                                                                    │
│  1. VISUALIZATION                                                  │
│     Can't plot 784D data, but can plot 2D!                         │
│     Reveal clusters and patterns to humans                         │
│                                                                    │
│  2. SPEED                                                          │
│     ML on 10 features is 100x faster than 1000 features            │
│     Less computation, less memory                                  │
│                                                                    │
│  3. NOISE REMOVAL                                                  │
│     Lower dimensions often capture signal, remove noise            │
│     Can improve model accuracy!                                    │
│                                                                    │
│  4. THE CURSE OF DIMENSIONALITY                                    │
│     As dimensions ↑, distance between points → same                │
│     Need exponentially more data in high dimensions                │
│                                                                    │
└────────────────────────────────────────────────────────────────────┘
```

PCA vs t-SNE vs UMAP

Method	Speed	Preserves	Best For
PCA	Very fast	Global structure	Initial exploration
t-SNE	Slow	Local clusters	Visualizing clusters
UMAP	Fast	Both local + global	Best overall

```
Same data, different methods:

PCA:                    t-SNE:                  UMAP:
┌─────────────┐        ┌─────────────┐         ┌─────────────┐
│ ●● ●●       │        │   ●●        │         │   ●●        │
│  ●●  ●●     │        │  ●●●        │         │   ●●        │
│    ▲▲       │        │             │         │             │
│   ▲▲        │        │   ▲▲▲       │         │  ▲▲         │
│  ■■         │        │  ▲▲         │         │ ▲▲▲         │
│ ■■          │        │      ■■■    │         │      ■■     │
└─────────────┘        │     ■■      │         │     ■■■     │
                       └─────────────┘         └─────────────┘

Linear projection      Clusters tight          Clusters + structure
```

Domain 5: Generative Models

Creating New Content

"Creativity is just connecting things." — Steve Jobs

The Generative AI Revolution

```
┌──────────────────────────────────────────────────────────────────────┐
│                    GENERATIVE AI TIMELINE                            │
├──────────────────────────────────────────────────────────────────────┤
│                                                                      │
│   2014: GANs invented                                                │
│         First realistic image generation                             │
│                                                                      │
│   2020: GPT-3 launches                                              │
│         Text generation goes mainstream                              │
│                                                                      │
│   2022: DALL-E 2, Stable Diffusion, Midjourney                      │
│         Anyone can generate images from text                         │
│                                                                      │
│   2022: ChatGPT launches                                            │
│         100M users in 2 months (fastest ever)                        │
│                                                                      │
│   2023: GPT-4, Claude, Gemini                                       │
│         Multimodal: text + images + code                             │
│                                                                      │
│   2024: Sora (video), Suno (music)                                  │
│         Generate any media type from text                            │
│                                                                      │
└──────────────────────────────────────────────────────────────────────┘
```

Task 22: Image Generation

What: Create new images from noise, text, or other images.

```
Text-to-Image (Stable Diffusion, DALL-E, Midjourney):

Prompt: "A robot painting                 Generated Image:
         a sunset, oil                    ┌─────────────────────┐
         painting style"                  │                     │
              │                           │  [AI Generated Art] │
              └──────────────────────────►│                     │
                                          │  [Beautiful AI      │
                                          │   generated art]    │
                                          └─────────────────────┘


Noise-to-Image (GANs, Diffusion):

Random Noise ──► Generator ──► Realistic Image
 [z ~ N(0,1)]                  (faces, landscapes, art...)
```

How Diffusion Models Work

```
┌──────────────────────────────────────────────────────────────────────┐
│                    DIFFUSION: THE CORE IDEA                          │
├──────────────────────────────────────────────────────────────────────┤
│                                                                      │
│   TRAINING (Forward process):                                        │
│   ──────────────────────────                                         │
│   Take image → gradually add noise → pure noise                      │
│                                                                      │
│   [Img] -> [Img+░] -> [Img+▒] -> [Img+▓] -> [Noise]                  │
│   Clean    Slight    Medium    Heavy    Pure                         │
│   image    noise     noise     noise    noise                        │
│                                                                      │
│   GENERATION (Reverse process):                                      │
│   ─────────────────────────────                                      │
│   Start with noise → gradually denoise → clean image                 │
│                                                                      │
│   [Noise] -> [Img+▓] -> [Img+▒] -> [Img+░] -> [Img]                  │
│   Pure       Heavy     Medium    Slight    Clean                     │
│   noise      noise     noise     noise     image!                    │
│                                                                      │
│   The model learns: "Given noisy image, predict the noise"           │
│                                                                      │
└──────────────────────────────────────────────────────────────────────┘
```

Task 23: Image Inpainting

What: Fill in missing or masked regions intelligently.

```
Original with hole:                  Inpainted result:
┌─────────────────────────┐         ┌─────────────────────────┐
│                         │         │                         │
│    Mtns ████████        │   -->   │    Mtns + sun + clouds  │
│       ████████          │         │       blue sky...       │
│                         │         │                         │
│    Trees House Trees    │         │    Trees House Trees    │
│                         │         │                         │
└─────────────────────────┘         └─────────────────────────┘

   (user painted a mask)              (AI filled it in)
```

Uses:

- Remove unwanted objects (photobombers!)
- Restore damaged/old photos
- Extend image boundaries (outpainting)

Task 24: Style Transfer

What: Apply the artistic style of one image to the content of another.

```
Content Image:          Style Image:           Result:
┌───────────────┐      ┌───────────────┐      ┌───────────────┐
│               │      │               │      │               │
│  [Photo of    │  +   │  [Van Gogh's  │  =   │  [Photo with  │
│   a bridge]   │      │   Starry      │      │   swirly      │
│               │      │   Night]      │      │   brushwork]  │
│               │      │               │      │               │
└───────────────┘      └───────────────┘      └───────────────┘

The model learns to separate:
- CONTENT: What objects are in the image (bridge, sky, water)
- STYLE: How they're rendered (brushstrokes, colors, texture)
```

Task 25: Super Resolution

What: Upscale low-resolution images while adding realistic detail.

```
Low Resolution (64×64):             High Resolution (512×512):
┌───────────────────┐               ┌──────────────────────────────┐
│                   │               │                              │
│   [Blurry,        │               │   [Sharp, detailed image     │
│    pixelated      │     ──▶       │    with realistic texture,   │
│    face]          │   AI Magic    │    pores, hair strands]      │
│                   │               │                              │
└───────────────────┘               └──────────────────────────────┘

Traditional upscaling: Just makes pixels bigger (still blurry)
AI upscaling: Adds plausible detail that wasn't there!
```

Ethical note: Super resolution "hallucinates" detail. The added details are plausible but not necessarily accurate. Not suitable for forensics or legal evidence!

Domain 6: Self-Supervised Learning

The Secret Sauce of Modern AI

"Give me a lever long enough and I shall move the world." — Archimedes

The Self-Supervised Revolution

```
┌─────────────────────────────────────────────────────────────────────┐
│                    THE LABELING BOTTLENECK                          │
├─────────────────────────────────────────────────────────────────────┤
│                                                                     │
│   SUPERVISED LEARNING:                                              │
│   ───────────────────                                               │
│   Need millions of labeled examples                                 │
│   Labeling is EXPENSIVE and SLOW                                    │
│   Limited by human annotation capacity                              │
│                                                                     │
│   ImageNet: 14 million images                                       │
│   Cost: ~$500,000 and years of work!                                │
│                                                                     │
│   SELF-SUPERVISED LEARNING:                                         │
│   ────────────────────────                                          │
│   Create labels FROM the data itself                                │
│   "Free" supervision from data structure                            │
│   Can use BILLIONS of examples                                      │
│                                                                     │
│   GPT-3: 45 TB of text                                              │
│   Cost: Compute only (no labeling!)                                 │
│                                                                     │
└─────────────────────────────────────────────────────────────────────┘
```

Task 26: Masked Language Modeling (BERT-style)

What: Predict the hidden word(s) — fill in the blank.

```
Training example:

Original:  "The cat sat on the mat."
Masked:    "The cat sat on the [MASK]."
                                   │
                                   ▼
                         ┌─────────────────┐
                         │     BERT        │
                         └────────┬────────┘
                                  │
                                  ▼
Predictions:    "mat"   (0.45)  ← Correct!
                "floor" (0.22)
                "couch" (0.15)
                "bed"   (0.08)
                ...
```

BERT was trained on **3.3 billion words** from Wikipedia and books, just playing fill-in-the-blank!

Task 27: Next Token Prediction (GPT-style)

What: Predict what comes next in a sequence.

```
Input:  "The capital of France is"
                                   │
                                   ▼
                         ┌────────────────┐
                         │     GPT        │
                         └────────┬───────┘
                                  │
                                  ▼
Next token distribution:
         "Paris"  (0.89)  ← Most likely
         "the"    (0.03)
         "in"     (0.02)
         "a"      (0.01)
         ...
```

> **GPT, Claude, Gemini, and all LLMs** are trained with just this one objective — repeated trillions of times! The simplicity is the brilliance.

BERT vs GPT: Key Differences

```
┌───────────────────────────────────────────────────────────────────────┐
│                        BERT vs GPT                                     │
├───────────────────────────────────────────────────────────────────────┤
│                                                                        │
│   BERT (Bidirectional)              GPT (Autoregressive)               │
│   ────────────────────              ─────────────────────              │
│                                                                        │
│   "The [MASK] sat on mat"           "The cat sat on"→ "the"→ "mat"    │
│        ↑↓↑↓↑                            ────────────────────►         │
│   Looks both directions             Only looks backward               │
│                                                                        │
│   Best for:                         Best for:                         │
│   • Understanding text              • Generating text                 │
│   • Classification                  • Chat/dialogue                   │
│   • Question answering              • Code completion                 │
│   • Named entity recognition        • Creative writing                │
│                                                                        │
│   Can't generate text well          Can generate, but slower          │
│   (doesn't predict in order)        (one token at a time)             │
│                                                                        │
└───────────────────────────────────────────────────────────────────────┘
```

Task 28: Contrastive Learning

What: Learn that different views of the same image should have similar embeddings.

```
Original Image:
    ┌─────────────┐
    │    [Cat]    │
    └──────┬──────┘
           │
    ┌──────┴──────┐      Create different "views"
    ▼             ▼      (augmentations)
┌─────────┐  ┌─────────┐
│ [Cat]   │  │  [Cat]  │
│(cropped)│  │(rotated)│
└────┬────┘  └────┬────┘
     │            │
     ▼            ▼
   [emb1]      [emb2]      These should be SIMILAR!

Meanwhile: embeddings of DIFFERENT images should be DIFFERENT!

   [cat_emb] ←──────────────────────→ [dog_emb]
              Push apart!
```

Contrastive Learning: The Big Picture

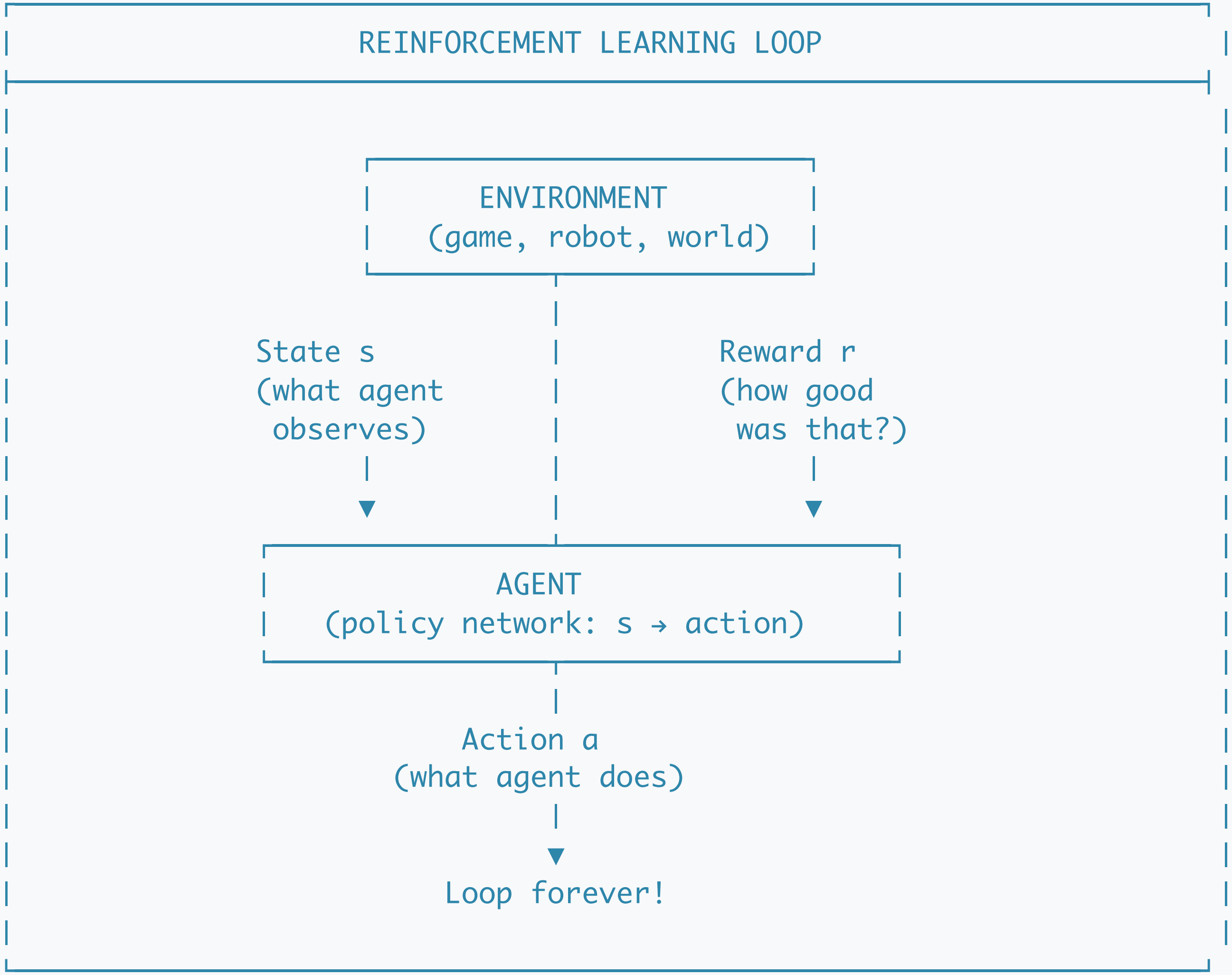
```
┌─────────────────────────────────────────────────────────────────────┐
│                    CONTRASTIVE LEARNING                             │
├─────────────────────────────────────────────────────────────────────┤
│                                                                     │
│  Key Insight:                                                       │
│  ────────────                                                       │
│  We don't need labels to learn good representations!                │
│  Just need to know: "These are the same" vs "These are different"   │
│                                                                     │
│  Training:                                                          │
│  ─────────                                                          │
│  • Take image → create 2 augmented versions (positive pair)         │
│  • Other images in batch = negative pairs                           │
│  • Learn: positives close, negatives far                            │
│                                                                     │
│  Result:                                                            │
│  ───────                                                            │
│  An encoder that maps similar images to similar embeddings          │
│  Can then use these embeddings for ANY downstream task!             │
│  Often matches supervised learning with just 1% of labels!          │
│                                                                     │
│  Famous methods: SimCLR, MoCo, CLIP                                 │
│                                                                     │
└─────────────────────────────────────────────────────────────────────┘
```

Domain 7: Reinforcement Learning

Learning by Doing

"Experience is the teacher of all things." — Julius Caesar

The RL Framework



REINFORCEMENT LEARNING LOOP

ENVIRONMENT
(game, robot, world)

State s
(what agent
observes)

Reward r
(how good
was that?)

AGENT
(policy network: s → action)

Action a
(what agent does)

Loop forever!

Task 29: Game Playing

What: Learn optimal strategy through trial and error.

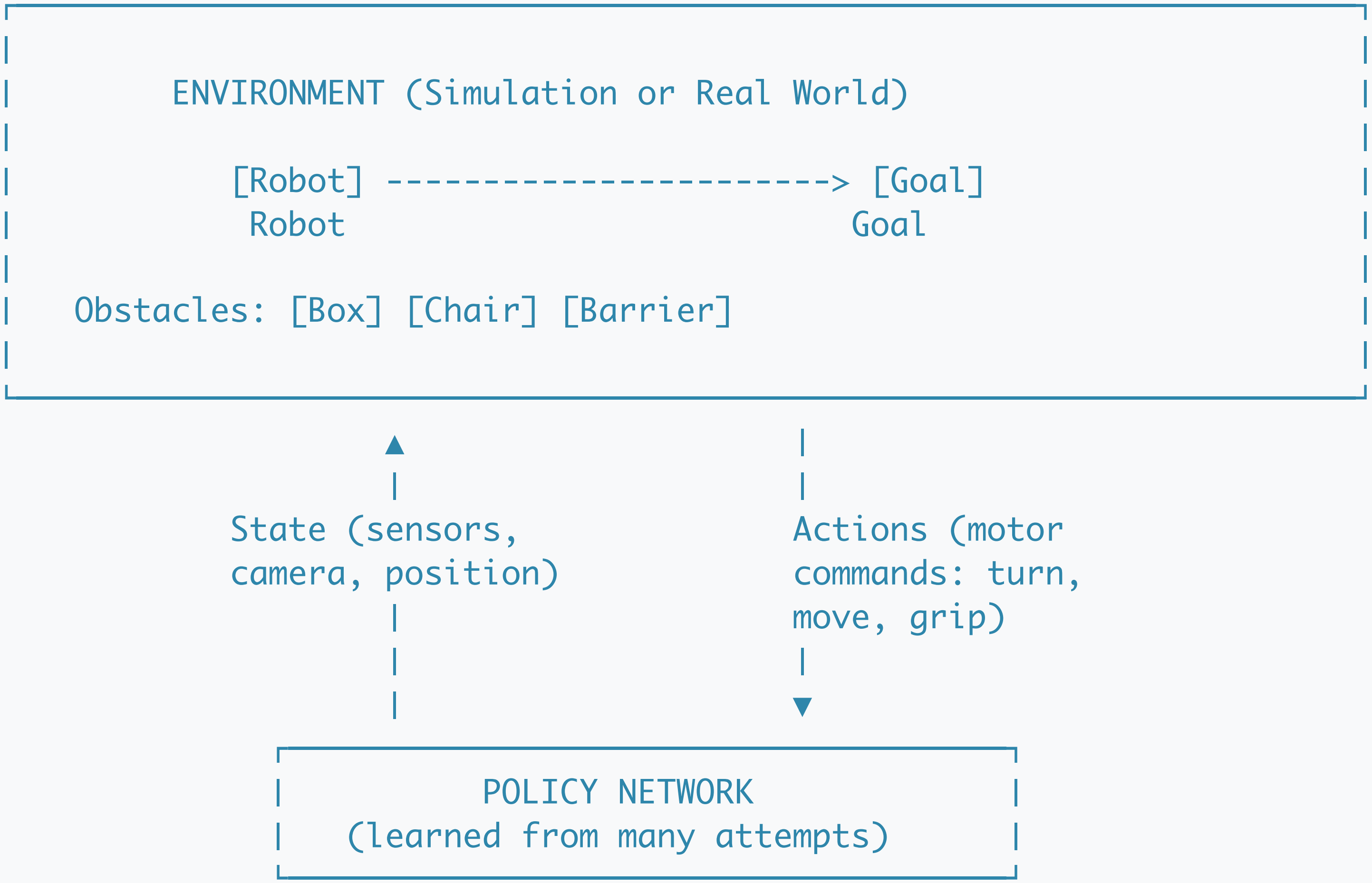
```
Game State (Chess):              Agent Decision:

┌──────────────────────┐
│ ♜ ♞ ♝ ♛ ♚ ♝ ♞ ♜    │          ┌──────────────────┐
│ ♟ ♟ ♟ ♟ ♟ ♟ ♟ ♟    │   ──►    │  Best move:      │
│ . . . . . . . .      │          │  e2 → e4         │
│ . . . . . . . .      │          │                  │
│ . . . . . . . .      │          │  Evaluation:     │
│ . . . . . . . .      │          │  +0.3 pawns      │
│ ♙ ♙ ♙ ♙ ♙ ♙ ♙ ♙    │          └──────────────────┘
│ ♖ ♘ ♗ ♕ ♔ ♗ ♘ ♖    │
└──────────────────────┘


AlphaGo/AlphaZero: Learned by playing MILLIONS of games against itself!
No human games needed - pure self-play!
```

RL Milestones in Games

```
┌─────────────────────────────────────────────────────────────────────┐
│                    RL GAME-PLAYING ACHIEVEMENTS                      │
├─────────────────────────────────────────────────────────────────────┤
│                                                                      │
│   1992: TD-Gammon                                                   │
│   ─────────────────                                                  │
│   Backgammon at world champion level                                 │
│   First major RL success!                                            │
│                                                                      │
│   2013: DQN (Atari)                                                 │
│   ────────────────                                                   │
│   Superhuman at 29 Atari games                                       │
│   Raw pixels as input!                                               │
│                                                                      │
│   2016: AlphaGo                                                     │
│   ────────────────                                                   │
│   Beats world champion Lee Sedol at Go                               │
│   Game with 10^170 possible positions!                               │
│                                                                      │
│   2019: AlphaStar                                                   │
│   ─────────────────                                                  │
│   Grandmaster level at StarCraft II                                  │
│   Real-time, imperfect information, complex strategy                 │
│                                                                      │
└─────────────────────────────────────────────────────────────────────┘
```

Task 30: Robot Control

What: Learn to move and interact in the physical world.



```
        ENVIRONMENT (Simulation or Real World)

           [Robot] -----------------------> [Goal]
            Robot                           Goal

   Obstacles: [Box] [Chair] [Barrier]

                    ▲                    |
                    |                    |
           State (sensors,         Actions (motor
           camera, position)       commands: turn,
                    |              move, grip)
                    |                    |
                    |                    ▼

                    POLICY NETWORK
             (learned from many attempts)
```

Reward: +10 for reaching goal, -1 for bumping, -0.01 per step

Real-World RL Applications

Robotics

- Robot manipulation (picking objects)
- Drone navigation
- Self-balancing robots
- Walking robots (Boston Dynamics)

Games

- Video game AI
- Board game engines
- Game testing automation

Beyond Games

- **Data center cooling** (Google: 40% energy savings)
- **Chip design** (Google, NVIDIA)
- **Trading** (quantitative finance)
- **Recommendations** (long-term engagement)
- **RLHF** (making LLMs helpful & safe!)

> **ChatGPT uses RLHF** (Reinforcement Learning from Human Feedback) to learn to be helpful rather than just predicting text!

Domain 8: Multimodal Tasks

Combining Vision + Language

"The whole is greater than the sum of its parts." — Aristotle

The Multimodal Revolution

```
┌──────────────────────────────────────────────────────────────────────┐
│                    MULTIMODAL = MULTIPLE MODALITIES                  │
├──────────────────────────────────────────────────────────────────────┤
│                                                                      │
│   MODALITY = Type of data                                            │
│   ───────────────────────                                            │
│   ● Text (words, sentences)                                          │
│   ● Images (photos, diagrams)                                        │
│   ● Audio (speech, music)                                            │
│   ● Video (sequences of images + audio)                              │
│                                                                      │
│   MULTIMODAL MODELS:                                                 │
│   ──────────────────                                                 │
│   ● GPT-4V: Text + Images                                            │
│   ● Gemini: Text + Images + Audio + Video                            │
│   ● CLIP: Connects text and images                                   │
│   ● Claude: Text + Images + Documents                                │
│                                                                      │
│   The trend: One model to rule them all!                             │
│                                                                      │
└──────────────────────────────────────────────────────────────────────┘
```

Task 31: Visual Question Answering (VQA)

What: Answer questions about images using both visual and language understanding.

```
Image:                              Questions & Answers:

┌───────────────────────┐
│                       │        Q: "How many people are
│    Man Woman Dog          │            in the image?"
│                       │        A: "Two people"
│  [People walking      │
│   a dog in a park]    │        Q: "What animal is there?"
│                       │        A: "A dog"
│    Tree    Tree       │
│                       │        Q: "What are they doing?"
│                       │        A: "Walking their dog
│                       │            in a park"
└───────────────────────┘


Requires BOTH:
- Understanding image content (computer vision)
- Understanding question (NLP)
- Reasoning to connect them!
```

Task 32: Image Captioning

What: Generate natural language description of an image.

```
Image:                              Generated Caption:

┌───────────────────────┐
│                       │
│   [Runners]           │   -->   "A group of runners
│                       │          participating in a city
│   [Marathon scene     │          marathon on a sunny day,
│    with crowds and    │          with spectators cheering
│    city buildings]    │          along the street and tall
│                       │          buildings in the background."
│   [Crowds][Buildings]  │
│                       │
└───────────────────────┘


The inverse of VQA:
Instead of answering questions, generate descriptions!
```

Task 33: Text-to-Video

What: Generate video from text description.

```
Prompt: "A golden retriever running through a field
         of sunflowers on a sunny day, slow motion"
                    │
                    ▼
            ┌─────────────────┐
            │  Video Model    │
            │  (Sora, Runway, │
            │   Pika, etc.)   │
            └────────┬────────┘
                     │
                     ▼
    ┌───────┐ ┌───────┐ ┌───────┐ ┌───────┐     ┌───────┐
    │Frame 1│ │Frame 2│ │Frame 3│ │Frame 4│ ... │Frame N│
    │ [Dog] │ │ [Dog] │ │ [Dog] │ │ [Dog] │     │ [Dog] │
    │ Field │ │ Field │ │ Field │ │ Field │     │ Field │
    └───────┘ └───────┘ └───────┘ └───────┘     └───────┘

                  Temporally consistent video!
```

CLIP: The Foundation of Multimodal AI

```
┌─────────────────────────────────────────────────────────────────────┐
│                    CLIP: Connecting Text and Images                 │
├─────────────────────────────────────────────────────────────────────┤
│                                                                     │
│   Training Data: 400 million (image, caption) pairs from internet   │
│                                                                     │
│   ┌─────────────┐         ┌─────────────┐                           │
│   │    Image    │         │    Text     │                           │
│   │   Encoder   │         │   Encoder   │                           │
│   └──────┬──────┘         └──────┬──────┘                           │
│          │                       │                                  │
│          ▼                       ▼                                  │
│    [image_emb]   ←─ should match ─→   [text_emb]                    │
│                                                                     │
│   "A dog playing     →    [0.23, -0.41, 0.87, ...]                  │
│    in the snow"           Shared embedding space!                   │
│                                                                     │
│   Result: Can search images with text, or text with images!         │
│   Powers: DALL-E, Stable Diffusion, image search, and more          │
│                                                                     │
└─────────────────────────────────────────────────────────────────────┘
```

Domain 9: Tabular & Time Series

The Classic ML Tasks

"Not everything that counts can be counted, but data often helps."

Task 34-35: Regression & Classification on Tables

Tabular Regression:

```
┌────────┬──────┬────────┐
│ Beds   │ SqFt │ Price? │
├────────┼──────┼────────┤
│ 3      │ 1500 │ ???    │
│ 4      │ 2200 │ ???    │
│ 2      │ 900  │ ???    │
└────────┴──────┴────────┘
          │
          ▼
  Predict: $425,000

Output: Continuous number
```

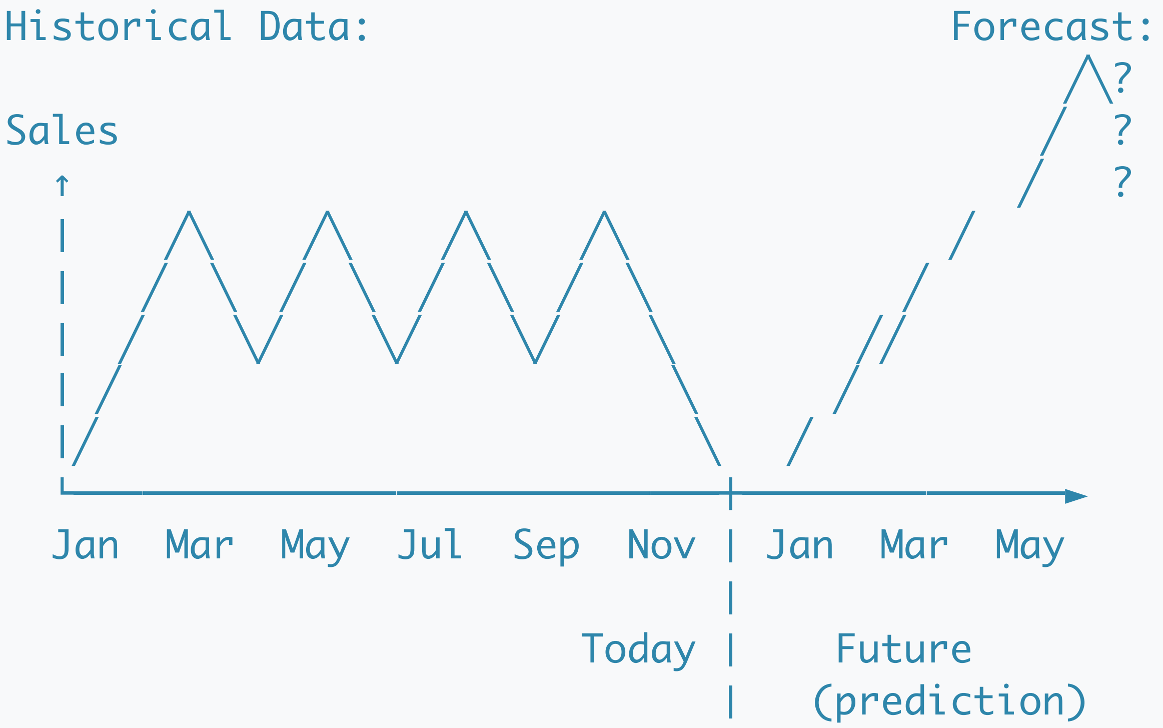
Tabular Classification:

```
┌─────┬───────┬─────────┐
│ Age │ Income│ Default?│
├─────┼───────┼─────────┤
│ 35  │ 75K   │ ???     │
│ 52  │ 120K  │ ???     │
│ 28  │ 45K   │ ???     │
└─────┴───────┴─────────┘
          │
          ▼
  Predict: Yes / No

Output: Category
```

> For tabular data, **gradient boosting (XGBoost, LightGBM)** often beats deep learning! Simpler, faster, and more interpretable.

Task 36: Time Series Forecasting

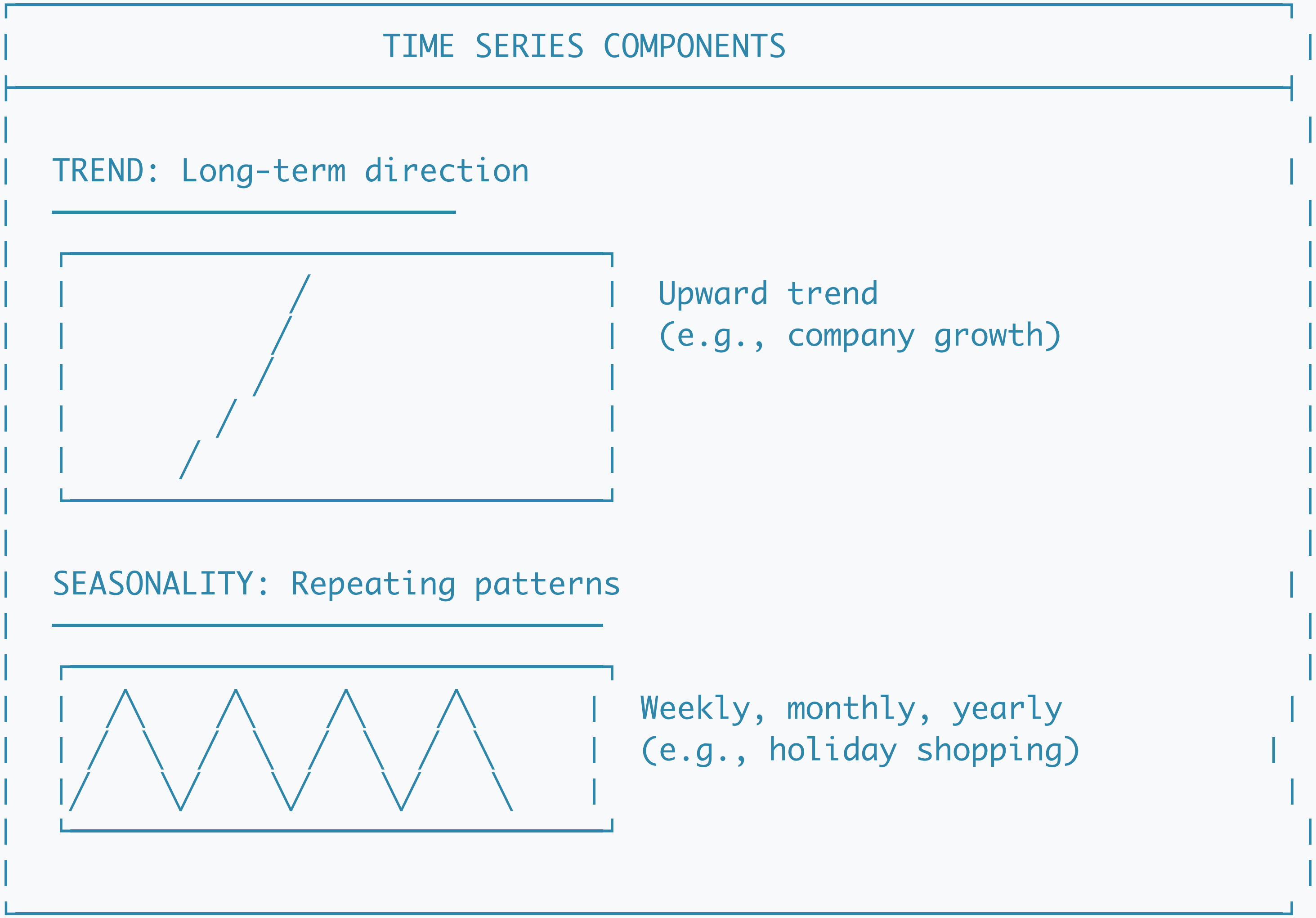
What: Predict future values from historical patterns.



Components to model:

- Trend (overall direction)
- Seasonality (repeating patterns)
- Noise (random variation)

Time Series: Key Patterns



TIME SERIES COMPONENTS

TREND: Long-term direction

Upward trend
(e.g., company growth)

SEASONALITY: Repeating patterns

Weekly, monthly, yearly
(e.g., holiday shopping)

Task 37: Recommendation Systems

What: Predict what users will like based on their history.

```
User-Item Matrix:                    Recommendations:
                                     ┌──────────────────────┐
         Movie1 Movie2 Movie3 Movie4 │ For User A:          │
User A      5      ?      3      ?    │  * Movie2 (pred: 4.2)│
User B      4      5      ?      2    │  * Movie4 (pred: 3.8)│
User C      ?      4      5      3    │                      │
                                     │ "Because you liked   │
                                     │  Movie1 and Movie3"  │
                                     └──────────────────────┘


Two main approaches:
● Collaborative: "Users like you also liked..."
● Content-based: "Similar items to ones you liked..."
```

Recommendation: The Netflix Problem

```
┌──────────────────────────────────────────────────────────────────────┐
│                    RECOMMENDATION CHALLENGES                          │
├──────────────────────────────────────────────────────────────────────┤
│                                                                       │
│  THE COLD START PROBLEM:                                              │
│  ─────────────────────────                                            │
│  New user: No history → What to recommend?                           │
│  New item: No ratings → Who might like it?                           │
│  Solution: Ask preferences, use demographics, popular items           │
│                                                                       │
│  THE SPARSITY PROBLEM:                                               │
│  ───────────────────────                                              │
│  Netflix: 200M users × 15K movies = 3 trillion possible ratings      │
│  Actual ratings: ~5 billion → 0.17% filled!                          │
│  Solution: Matrix factorization, embeddings                           │
│                                                                       │
│  THE FILTER BUBBLE:                                                  │
│  ──────────────────                                                   │
│  Only showing similar content → User misses diverse content           │
│  Solution: Exploration vs exploitation, diversity metrics             │
│                                                                       │
└──────────────────────────────────────────────────────────────────────┘
```

Summary: The ML Task Landscape

```
┌──────────────────────────────────────────────────────────────────────┐
│                        ML TASK FAMILIES                              │
├──────────────────────────────────────────────────────────────────────┤
│                                                                      │
│  SUPERVISED             UNSUPERVISED        SELF-SUPERVISED          │
│  ──────────             ────────────        ───────────────          │
│  ● Classification       ● Clustering        ● Masked LM (BERT)       │
│  ● Regression           ● Dim. Reduction    ● Next Token (GPT)       │
│  ● Detection            ● Anomaly Det.      ● Contrastive (CLIP)     │
│  ● Segmentation                                                      │
│  ● Seq2Seq                                                           │
│                                                                      │
│  GENERATIVE             REINFORCEMENT       MULTIMODAL               │
│  ──────────             ─────────────       ──────────               │
│  ● Image Gen            ● Game Playing      ● VQA                    │
│  ● Text Gen             ● Robotics          ● Captioning             │
│  ● Video Gen            ● RLHF              ● Text-to-Image          │
│  ● Style Transfer                           ● Text-to-Video          │
│                                                                      │
└──────────────────────────────────────────────────────────────────────┘
```

Choosing the Right Task

```
┌─────────────────────────────────────────────────────────────────────┐
│                   DECISION FLOWCHART                                 │
├─────────────────────────────────────────────────────────────────────┤
│                                                                     │
│   What do you want to predict?                                      │
│              │                                                      │
│   ┌──────────┼──────────┬────────────┐                              │
│   ▼          ▼          ▼            ▼                              │
│ Category  Continuous  Location     New Content                      │
│   │         │           │             │                             │
│   ▼         ▼           ▼             ▼                             │
│ Classification Regression Detection  Generation                     │
│                                                                     │
│   Have labels?                                                      │
│   ├── Yes → Supervised                                              │
│   ├── No  → Unsupervised (clustering, anomaly)                      │
│   └── Can create from data → Self-supervised                        │
│                                                                     │
│   Need to take actions?                                             │
│   └── Yes → Reinforcement Learning                                  │
│                                                                     │
│   Multiple input types?                                             │
│   └── Yes → Multimodal                                              │
│                                                                     │
└─────────────────────────────────────────────────────────────────────┘
```

Key Takeaways

The 5 Things to Remember

1. **Every task = Input type + Output type**
   Define these clearly and you've defined your problem
2. **Same architectures work across domains**
   Transformers power text, images, audio, and more
3. **Self-supervised learning powers modern AI**
   GPT, BERT, CLIP — all learned from unlabeled data
4. **Start with the task → then choose the model**
   Don't pick a model first and force it to fit
5. **Real-world ML often combines multiple tasks**
   Self-driving cars: detection + segmentation + prediction + control

The ML Practitioner's Toolkit

Task Type	Go-To Models (2024)
Image Classification	ResNet, EfficientNet, ViT
Object Detection	YOLOv8, DETR, RT-DETR
Segmentation	SAM, Mask R-CNN
Text Classification	BERT, RoBERTa
Text Generation	GPT-4, Claude, Llama
Speech-to-Text	Whisper
Image Generation	Stable Diffusion, DALL-E
Tabular	XGBoost, LightGBM, TabNet
Time Series	Prophet, N-BEATS, TimeGPT
Recommendations	Two-Tower, DLRM

What's Next?

In the Labs:

- Lab 1-2: sklearn basics
- Lab 3: PyTorch & neural nets
- Lab 4-5: Build your own LLM
- Lab 6-7: Object detection

The Bigger Picture:

- Most tasks share core principles
- Transfer learning is key
- Start simple, add complexity
- The best model is the one you ship!

> Pick a task, find a dataset, and start building! The best way to learn ML is by doing.

Thank You!

"The best way to predict the future is to invent it." — Alan Kay

Resources

- Papers With Code (paperwithcode.com) — State-of-the-art models
- Hugging Face (huggingface.co) — Pre-trained models
- Kaggle (kaggle.com) — Datasets and competitions

Questions?