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                       │
│                                                                      │
└──────────────────────────────────────────────────────────────────────┘
```

The Universal ML Recipe

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

```
                ┌────────────────────────────┐
                │        EVERY ML TASK       │
                └────────────────────────────┘
                            │
                            ▼
┌──────────┐      ┌─────────────┐      ┌──────────┐
│  INPUT   │  ──► │    MODEL    │  ──► │  OUTPUT  │
│  (X)     │      │  f(X; θ)    │      │   (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 (x_1, y_1), 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.

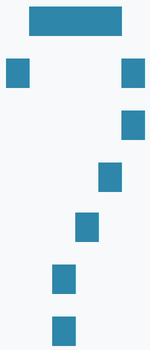
```
┌─────────────────┐
│                 │
│   [Photo of     │──→ "Golden Retriever"
│    a dog]       │    Confidence: 94.2%
│                 │
└─────────────────┘
```

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., 7x7)              │
│                                                          │
│  ┌───┬───┬───┬───┬───┬───┬───┐                           │
│  │   │   │   │   │   │   │   │                           │
│  ├───┼───┼───┼───┼───┼───┼───┤    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!

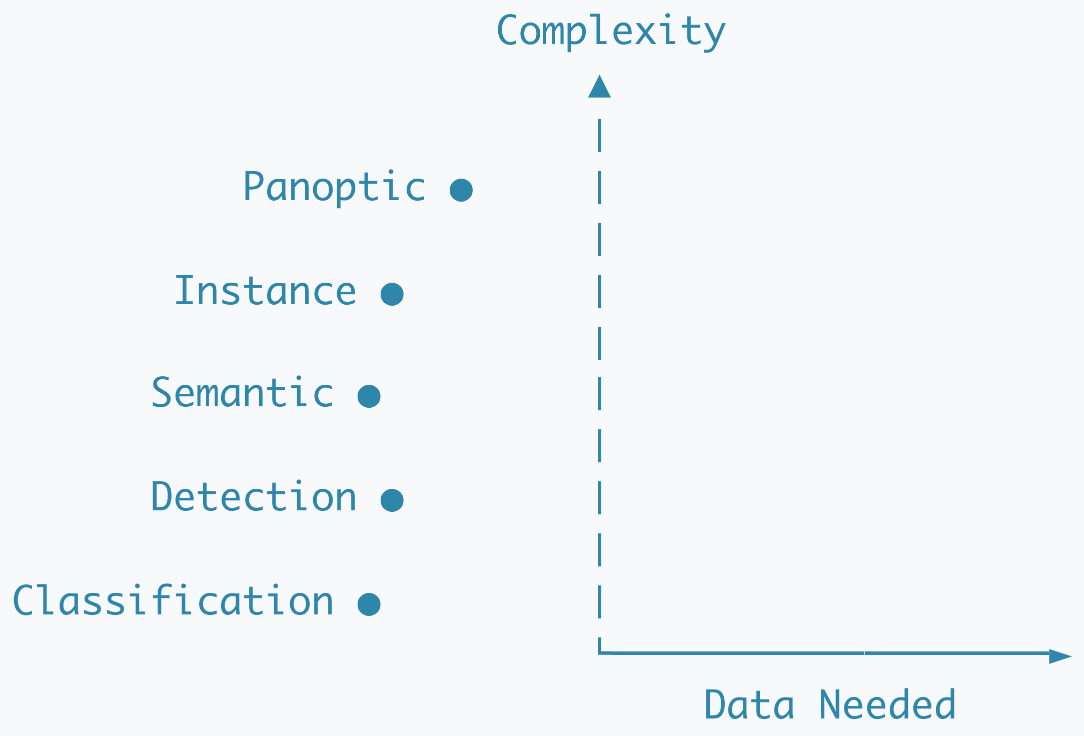
Panoptic Segmentation: The Complete Picture

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    |          ──►          ●  ●  ●  ← Shoulders
   |  standing   |                          |
   |   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:

┌───────┐    ┌─────────────┐    ┌─────────┐    ┌─────────┐    ┌──────┐
│ Audio │───→│ Spectrogram │───→│ Encoder │───→│ Decoder │───→│ Text │
└───────┘    └─────────────┘    └─────────┘    └─────────┘    └──────┘
 Waveform     Time-Frequency     Features       Language       Words
              representation                     model
```

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             │       Reward r             │
│     (what agent         │       (how good            │
│      observes)          │        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.

```
Historical Data:                         Forecast:
                                              /\?
Sales                                        /  ?
  ↑                                         /   ?
  |    /\    /\    /\    /\               /
  |   /  \  /  \  /  \  /  \            /
  |  /    \/    \/    \/    \         //
  | /                        \      /
  |/                          \   /
  └────────────────────────────┼──────────────►
   Jan  Mar  May  Jul  Sep  Nov | Jan  Mar  May
                                |
                          Today |   Future
                                |  (prediction)

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?