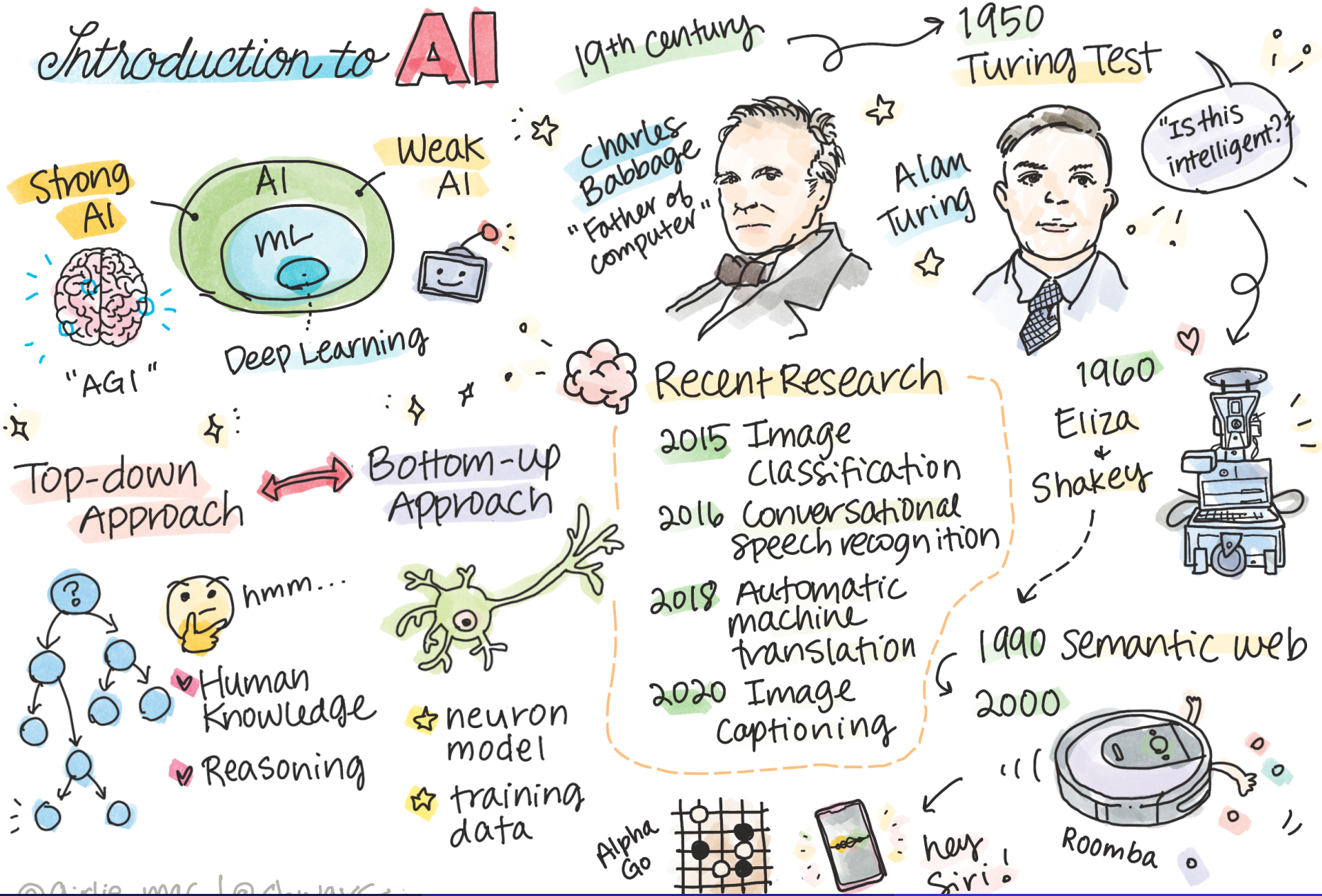
AI, Neural Network, and Machine Learning

Bagus Tris Atmaja

Part 1: Introduction to AI



What is Artificial Intelligence?

Artificial Intelligence is an exciting scientific discipline that studies how we can make computers exhibit intelligent behavior.

- Computers operate on algorithms: well-defined procedures
- Some tasks cannot be explicitly programmed
- Example: Determining age from a photograph

We cannot explicitly explain how we determine age, nor can we program a computer to do it traditionally.

Weak AI vs. Strong AI

Weak AI (Narrow AI)

- Designed for specific tasks
- Examples: Siri, Alexa, recommendation algorithms
- Highly specialized, lacks general intelligence

Strong AI (AGI)

- Human-level intelligence and understanding
- Can perform any intellectual task
- Currently theoretical - not yet achieved

Defining Intelligence

- No clear universal definition exists
- Connected to abstract thinking and self-awareness
- Difficult to measure objectively

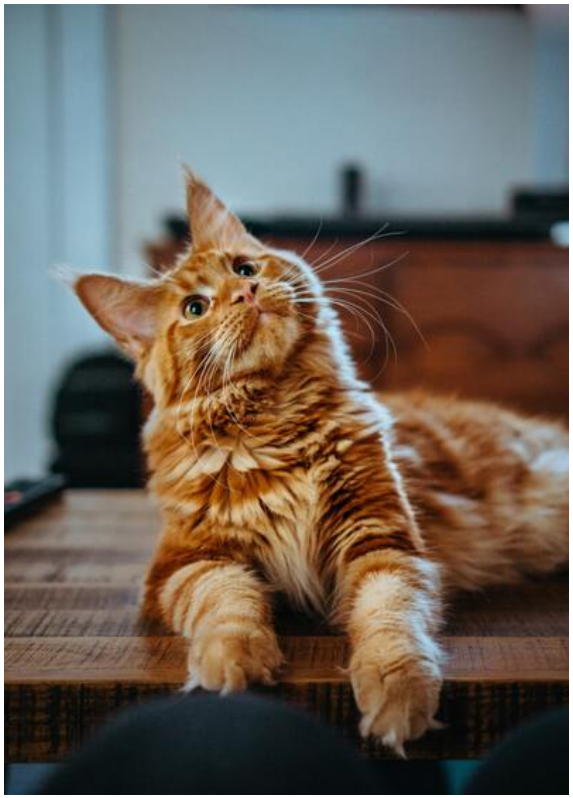


Figure 2: Is a cat intelligent? Different people give different answers!

The Turing Test

Proposed by Alan Turing as a test for machine intelligence:

- Compares system to human intelligence
- Human interrogator conducts text-based dialogue
- If interrogator cannot distinguish machine from human, system is considered intelligent

Eugene Goostman (2014):

- Convinced 30% of judges it was human
- Posed as 13-year-old Ukrainian boy
- Demonstrated cleverness, not true intelligence

Two Main Approaches to AI

Top-down Approach (Symbolic Reasoning)

- Models human reasoning processes
- Extracts knowledge from experts
- Represents knowledge in computer-readable form
- Uses explicit rules and logic

Bottom-up Approach (Neural Networks)

- Models structure of human brain
- Uses interconnected neurons
- Learns from training data
- Similar to how babies learn

Other Approaches

Emergent/Synergetic Approach:

- Complex behavior from simple agent interactions
- Intelligence emerges from reactive behaviors

Evolutionary Approach:

- Optimization based on evolution principles
- Genetic algorithms

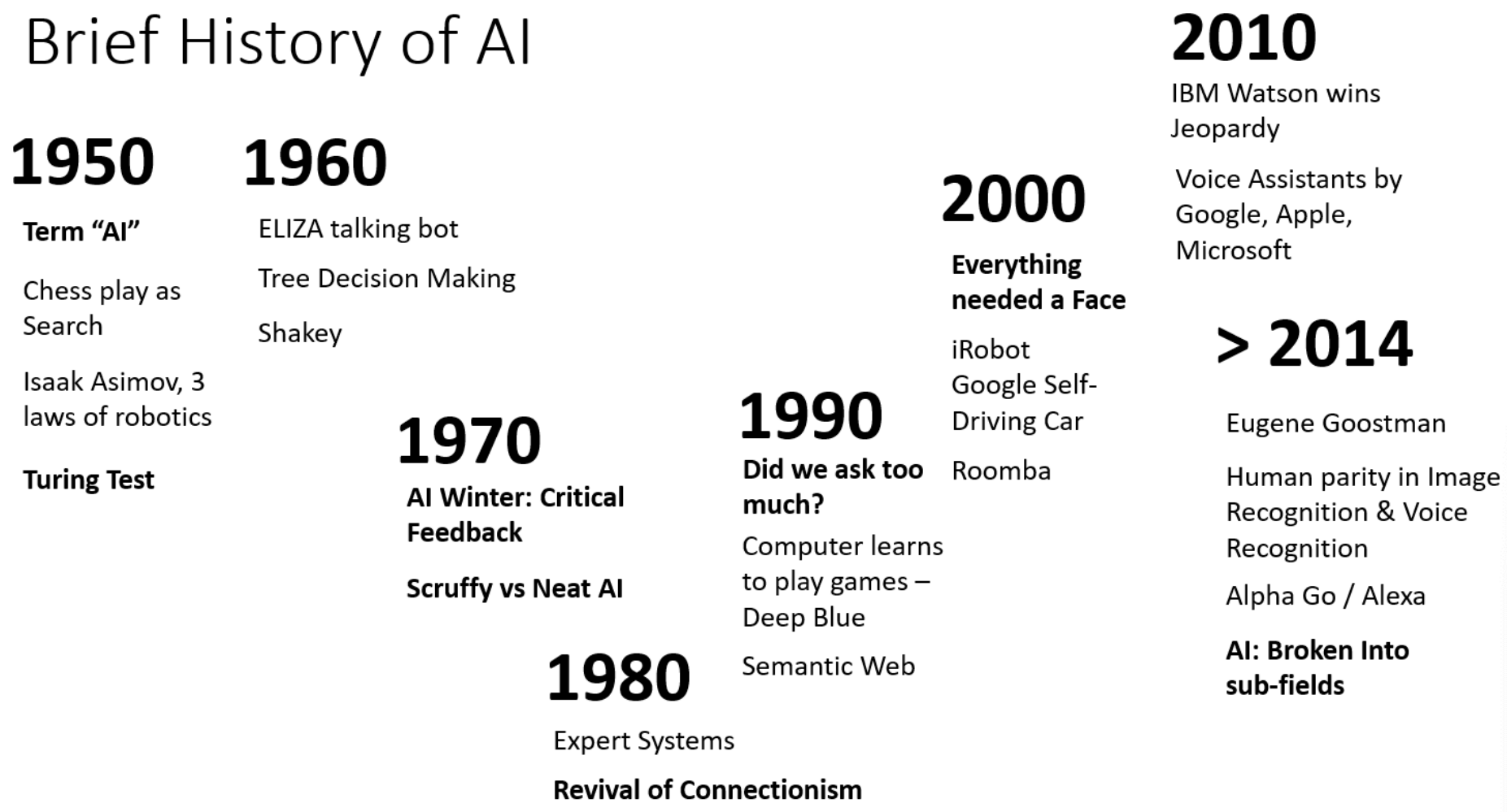


Figure 3: Brief History of AI

Brief History of AI

- **1950s-1960s:** Birth of AI, symbolic reasoning dominates
- **1970s:** AI Winter - expert systems too expensive
- **2010s:** Neural networks rise with big data
- **Today:** AI mostly synonymous with neural networks

Evolution: Chess Programs

Early Programs:

- Search-based algorithms
- Alpha-beta pruning

Middle Era:

- Case-based reasoning
- Learning from human matches

Modern Programs:

- Neural networks
- Reinforcement learning
- Self-play and learning from mistakes

Evolution: Conversational AI

Turing Test Evolution

1966 — ELIZA

- Tell me about your family
- My father takes care of me
- Who else from your family takes care of you?
- My mother
- Your mother?

2014 — Eugene Goostman

2021 — GPT/Turing NLG

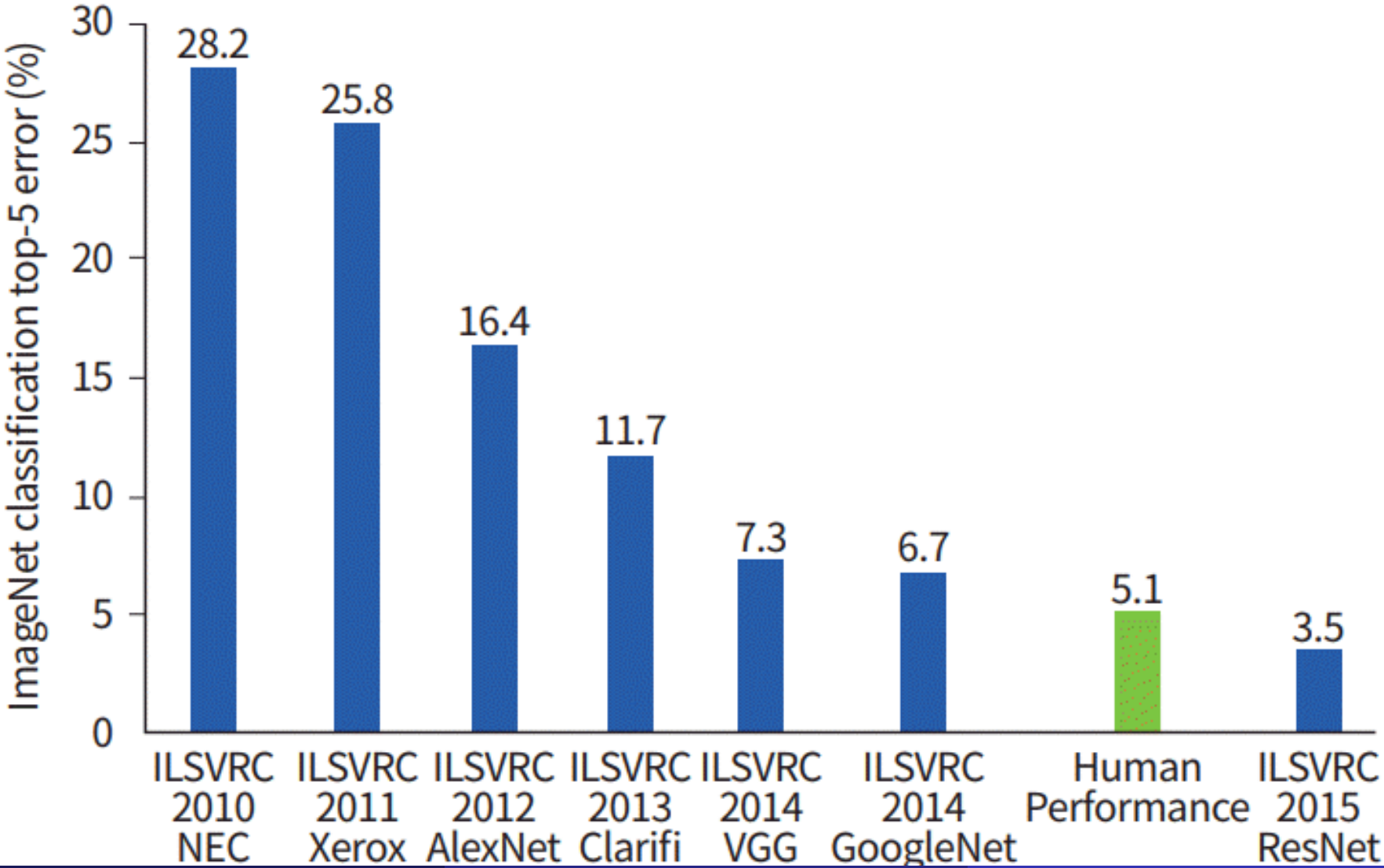
The best treatment against stress, according to British scientists, are kittens. In a recent research they found that 43% of people are likely to feel relaxed at a presence of a kitten…

Early: ELIZA - simple grammatical rules

Current: Cortana, Siri, Google Assistant - hybrid systems

Future: Complete neural-based models (GPT, Turing-NLG)

Recent AI Research (2012-2020)



Human Parity Achievements

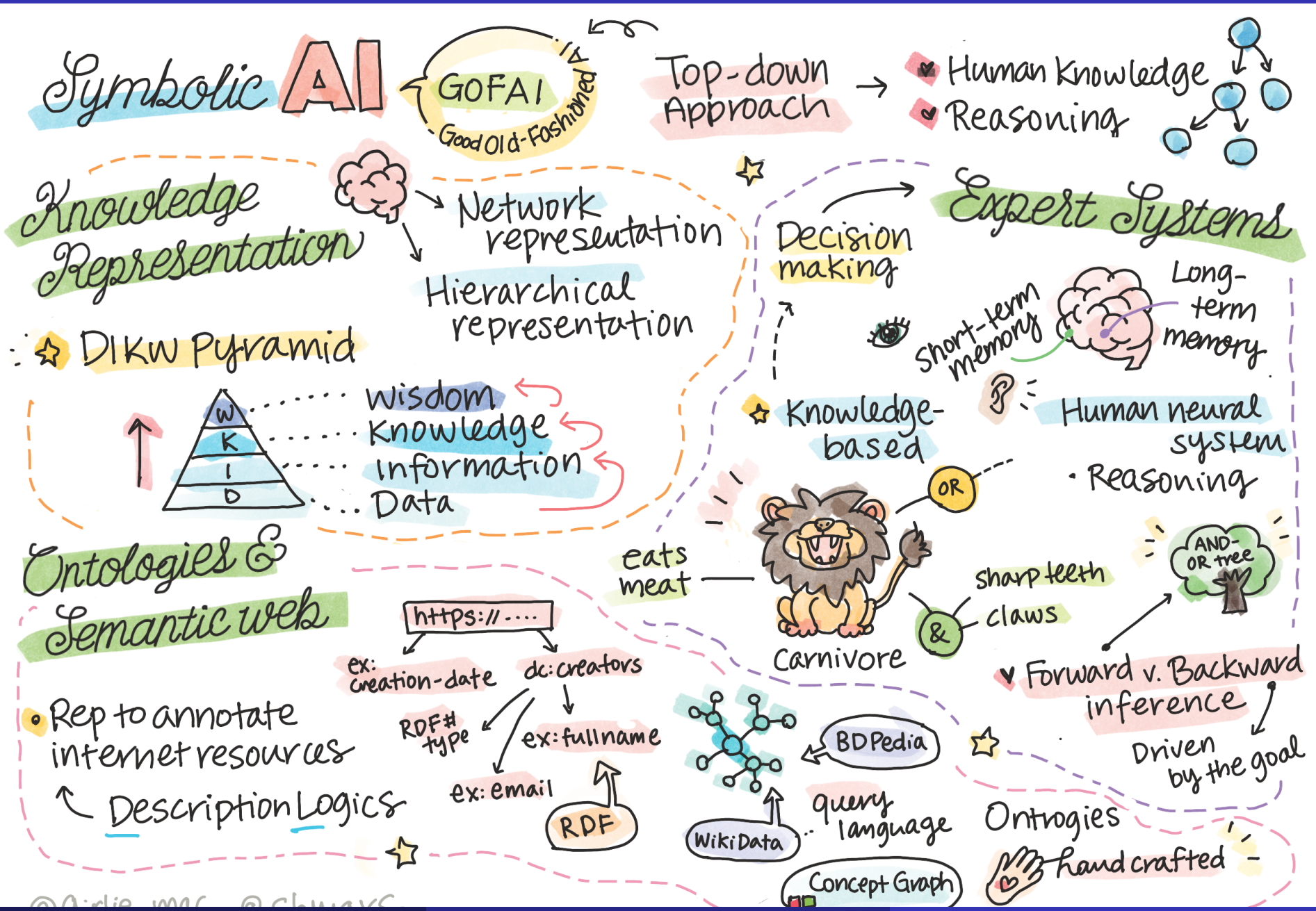
Year	Achievement
2015	Image Classification
2016	Conversational Speech Recognition
2018	Automatic Machine Translation
2020	Image Captioning

Recent Success: Large language models (BERT, GPT-3)

Key Takeaways - Part 1

1. AI aims to make computers exhibit intelligent behavior
2. Two main approaches: symbolic reasoning and neural networks
3. Neural networks currently dominate AI research
4. Massive datasets enabled recent breakthroughs
5. AI has achieved human parity in multiple domains
6. Large language models represent the cutting edge

Part 2: Knowledge Representation and Expert Systems



The Quest for Artificial Intelligence

- Based on search for knowledge
- Making sense of the world like humans do
- Early AI: Top-down approach to intelligent systems
- Two big ideas:
  - Knowledge Representation
  - Reasoning

What is Knowledge?

Differentiating Concepts:

- **Data**: What books contain (raw facts)
- **Information**: Interpreted data in our minds
- **Knowledge**: Understanding of the world
  - Obtained through active learning
  - Integrates information into our world model
  - Cannot simply be extracted from books

Knowledge is contained in our head and represents our understanding of the world

The DIKW Pyramid

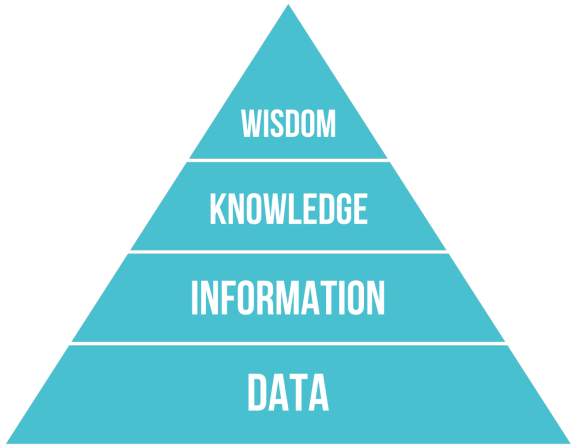


Figure 6: DIKW Pyramid

Four Levels of Understanding:

- **Data**: Physical representation (text, words)
- **Information**: Interpreted data
- **Knowledge**: Integrated understanding
- **Wisdom**: Meta-knowledge about when to apply knowledge

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Knowledge Representation Spectrum

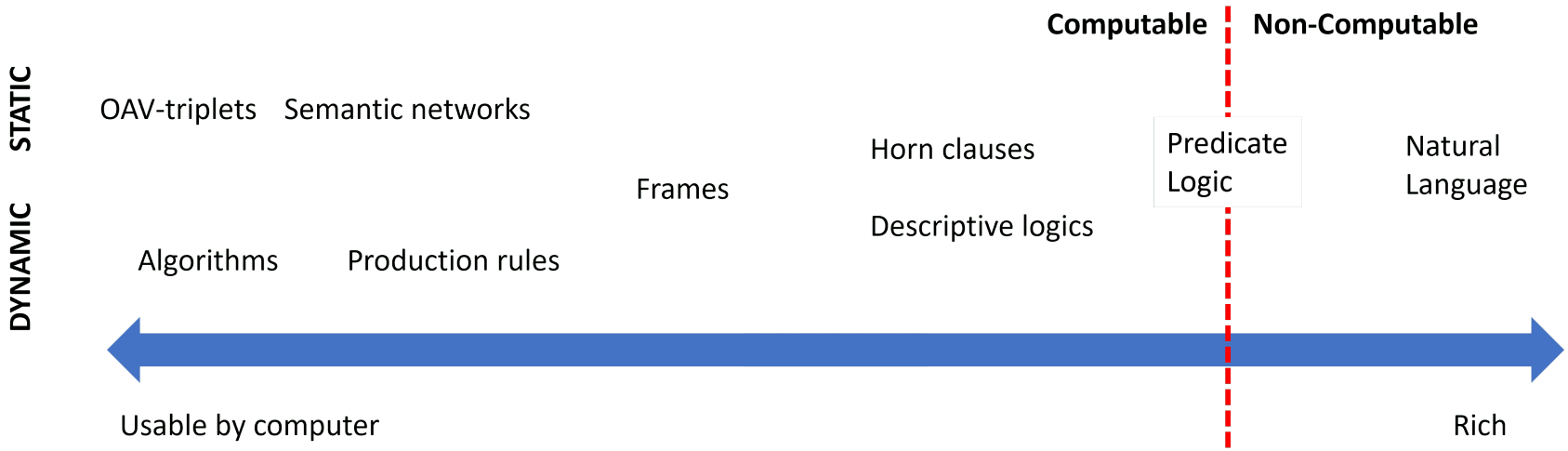


Figure 7: Knowledge representation spectrum

The Challenge:

- Left: Simple representations (algorithmic)
  - Effective for computers
  - Not flexible, non-human-like
- Right: Natural text
  - Most powerful
  - Cannot be used for automatic reasoning

Computer Knowledge Representations

Four Main Categories:

1. Network representations
2. Hierarchical representations
3. Procedural representations
4. Logic-based representations

Object-Attribute-Value Triplets

Example: Programming Languages

Object	Attribute	Value
Python	is	Untyped-Language
Python	invented-by	Guido van Rossum
Python	block-syntax	indentation
Untyped-Language	doesn't have	type definitions

Based on semantic networks (graphs of interrelated concepts)

Frame Representation: Python Example

Slot	Value	Default value	Interval
Name	Python		
Is-A	Untyped-Language		
Variable Case		CamelCase	
Program Length			5-5000 lines
Block Syntax	Indent		

Features:

- Objects/classes as frames with slots
- Default values and restrictions
- Hierarchical organization
- **Scenarios**: Special frames for temporal situations

Production Rules (IF-THEN statements)

```
IF patient has high fever
OR high C-reactive protein
THEN patient has inflammation
```

Key Points:

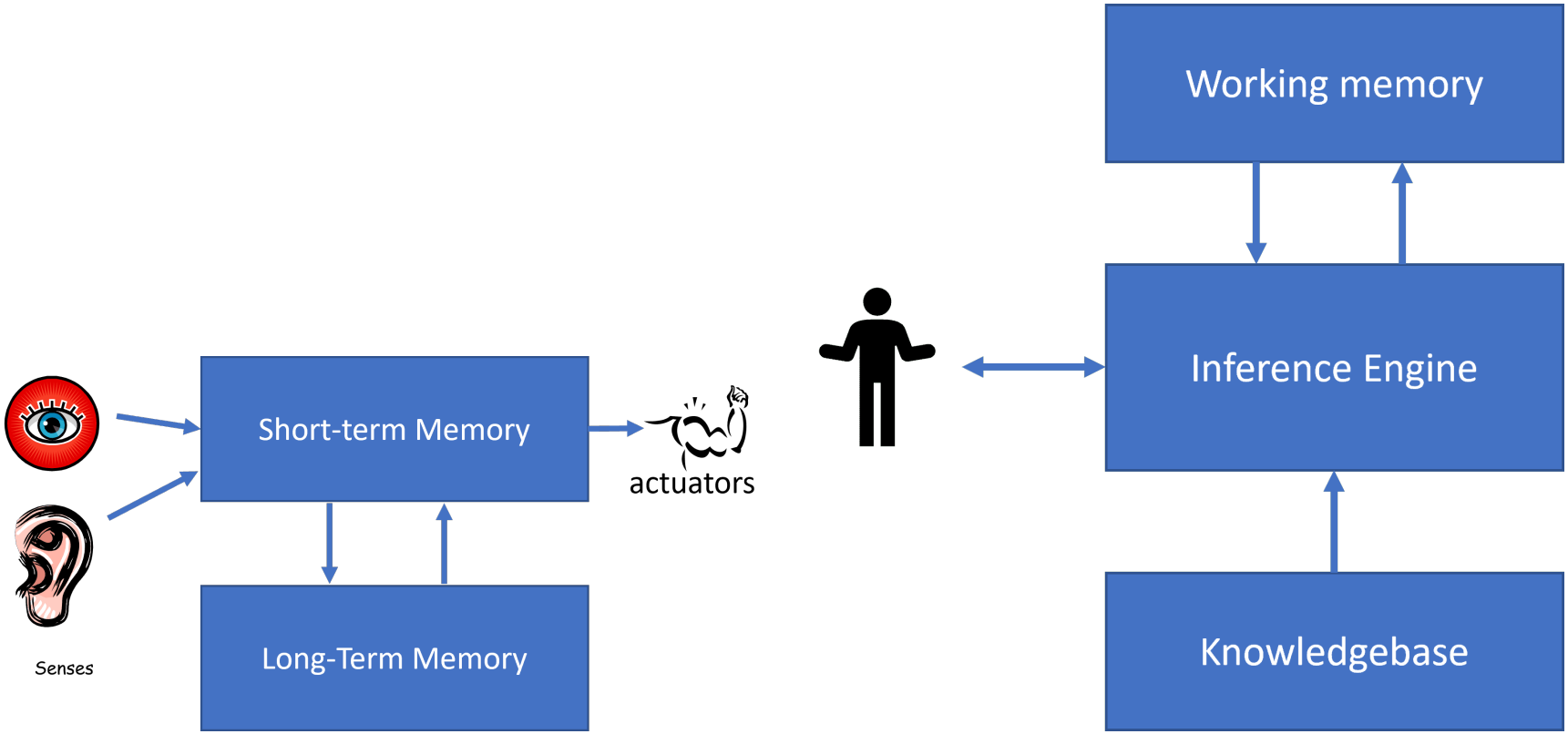
- Condition-action pairs
- Enable drawing conclusions
- Used for forward reasoning
- Algorithms as another form (rarely used directly)

Types of Logic:

- **Predicate Logic**
  - Too rich for computation
  - Subsets used (e.g., Horn clauses in Prolog)
- **Descriptive Logic**
  - Family of logical systems
  - For object hierarchies
  - Used in semantic web

Originally proposed by Aristotle for universal knowledge

Expert Systems



Definition:

- Computer systems acting as domain experts
- Based on extracted human expertise
- Contain inference engine for reasoning

Expert System Architecture

Three Main Components:

1. **Problem Memory** (Static Knowledge)
   - Current problem state
   - Temperature, symptoms, etc.
2. **Knowledge Base** (Dynamic Knowledge)
   - Long-term domain knowledge
   - Extracted from human experts
   - Navigation between states
3. **Inference Engine**
   - Orchestrates reasoning process
   - Asks questions when needed
   - Applies appropriate rules

Example: Animal Classification

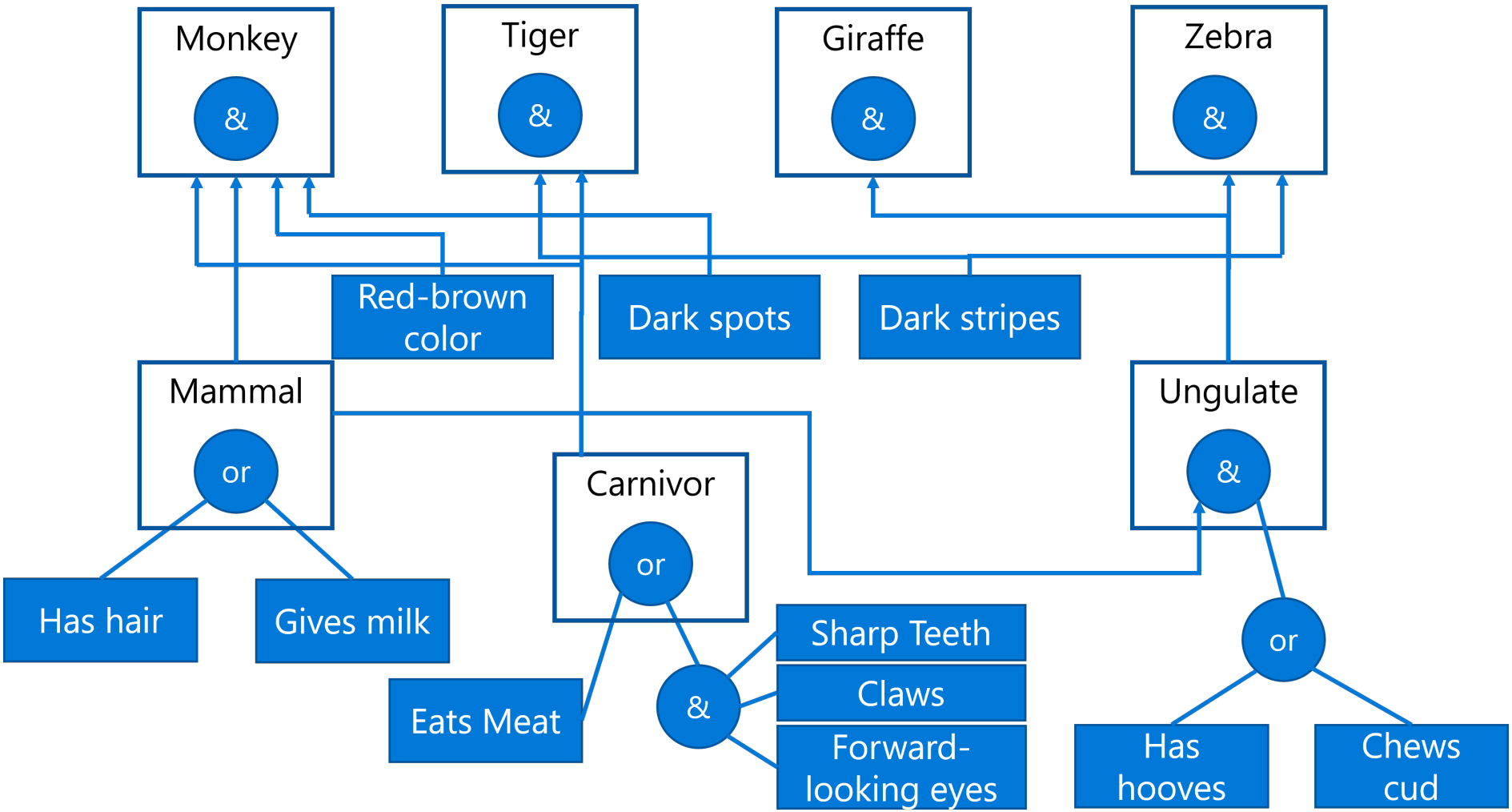


Figure 8: AND-OR Tree

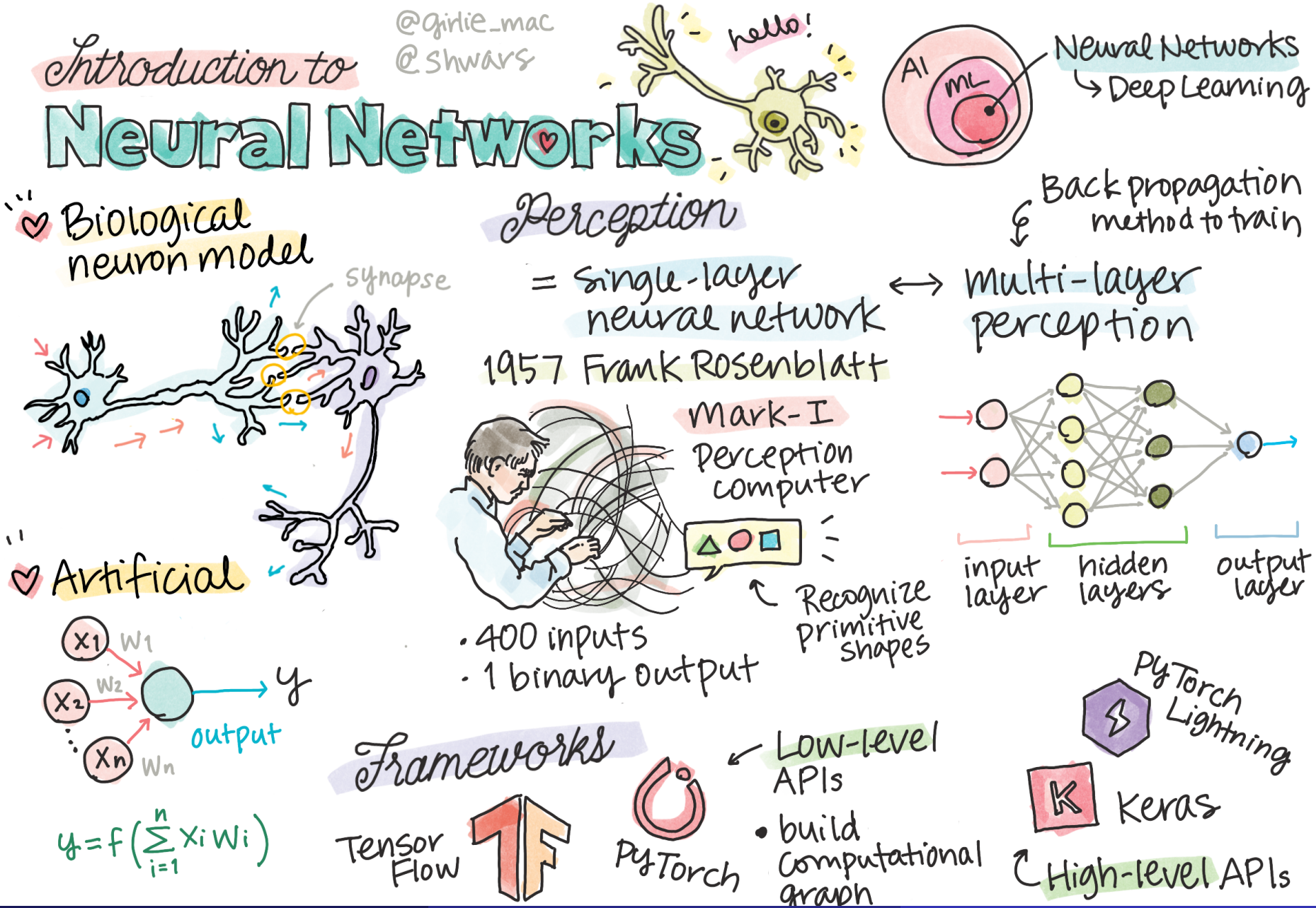
Key Takeaways - Part 2

Symbolic AI:

- AI != Only Machine Learning/Neural Networks
- Humans exhibit explicit reasoning
- Symbolic AI still valuable for:
  - Explainable decisions
  - Controlled system behavior
  - Tasks requiring justification

Current Status:

- Neural networks don't handle explicit reasoning
- Real-world projects still use symbolic approaches
- Hybrid approaches gaining popularity


Introduction to
Neural Networks
@girlie_mac
@shwars
hello!
AI
ML
Neural Networks
↳ Deep Learning
Biological neuron model
synapse
Artificial
x1 w1
x2 w2
xn wn
output
y
$y = f\left(\sum_{i=1}^{n} x_i w_i\right)$
Perception
= single-layer neural network
↔ multi-layer perception
1957 Frank Rosenblatt
Mark-I Perception computer
Recognize primitive shapes
• 400 inputs
• 1 binary output
Back propagation method to train
input layer
hidden layers
output layer
Frameworks
Tensor Flow
PyTorch
↙ Low-level APIs
• build computational graph
PyTorch Lightning
Keras
↳ High-level APIs

What are Neural Networks?

Achieving Intelligence through Training

- Train a **computer model** or **artificial brain**
- Mathematical models researched since mid-20th century
- Recently proved hugely successful
- Also called **Artificial Neural Networks** (ANNs)

Key Distinction:

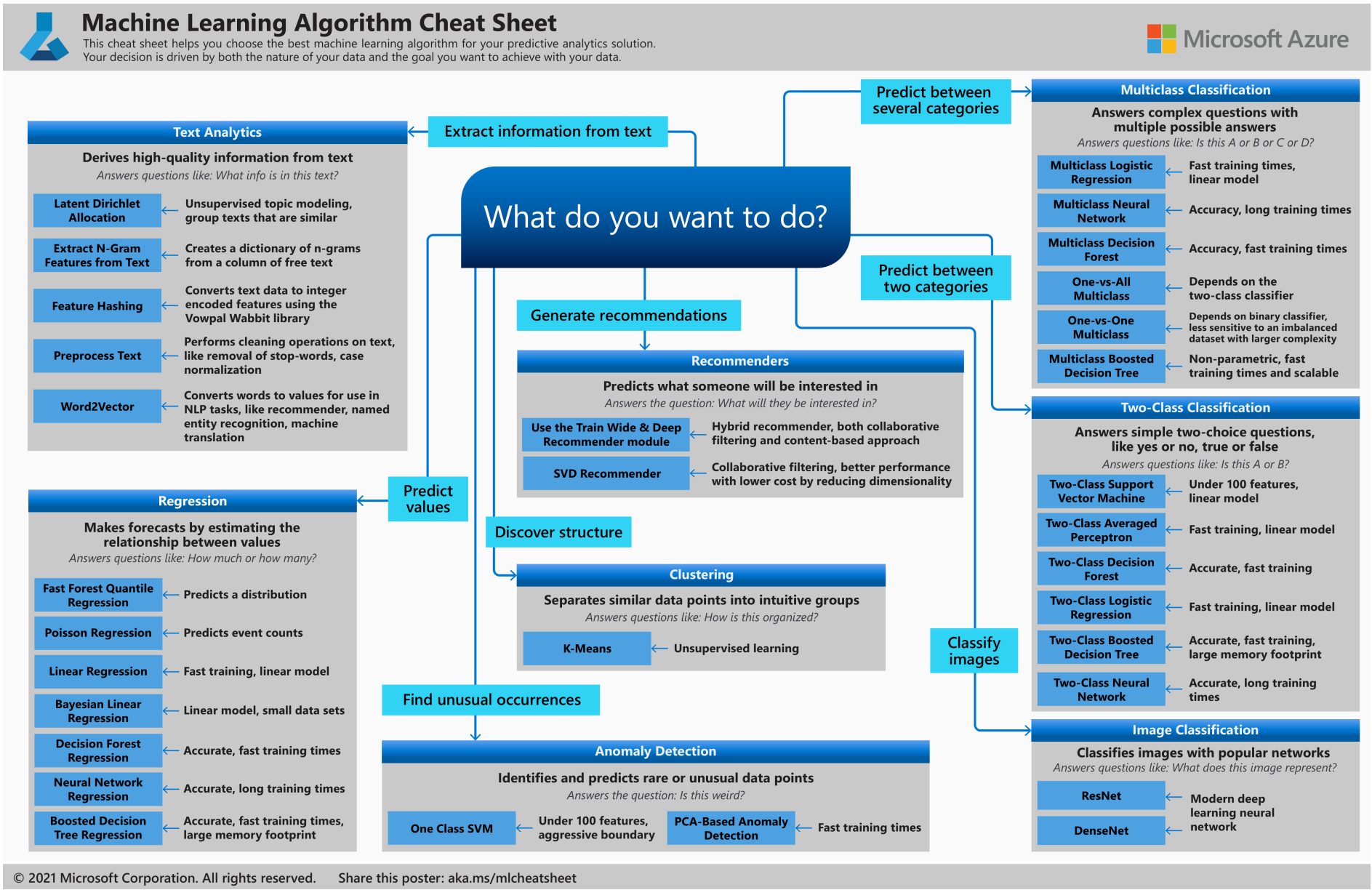
- We're talking about mathematical models
- Not real biological networks of neurons

Machine Learning Context

Neural Networks are part of Machine Learning

- Machine Learning: Use data to train computer models
- Large part of Artificial Intelligence
- Classical ML: SVM, KNN, Decision Trees, XGBoost

Machine Learning Tree



 Share this poster: aka.ms/mlcheatsheet

Machine Learning Fundamentals

Basic Setup:

- Dataset of examples: **X**
- Corresponding output values: **Y**
- Examples: N-dimensional vectors (features)
- Outputs: Labels

Data Representation:

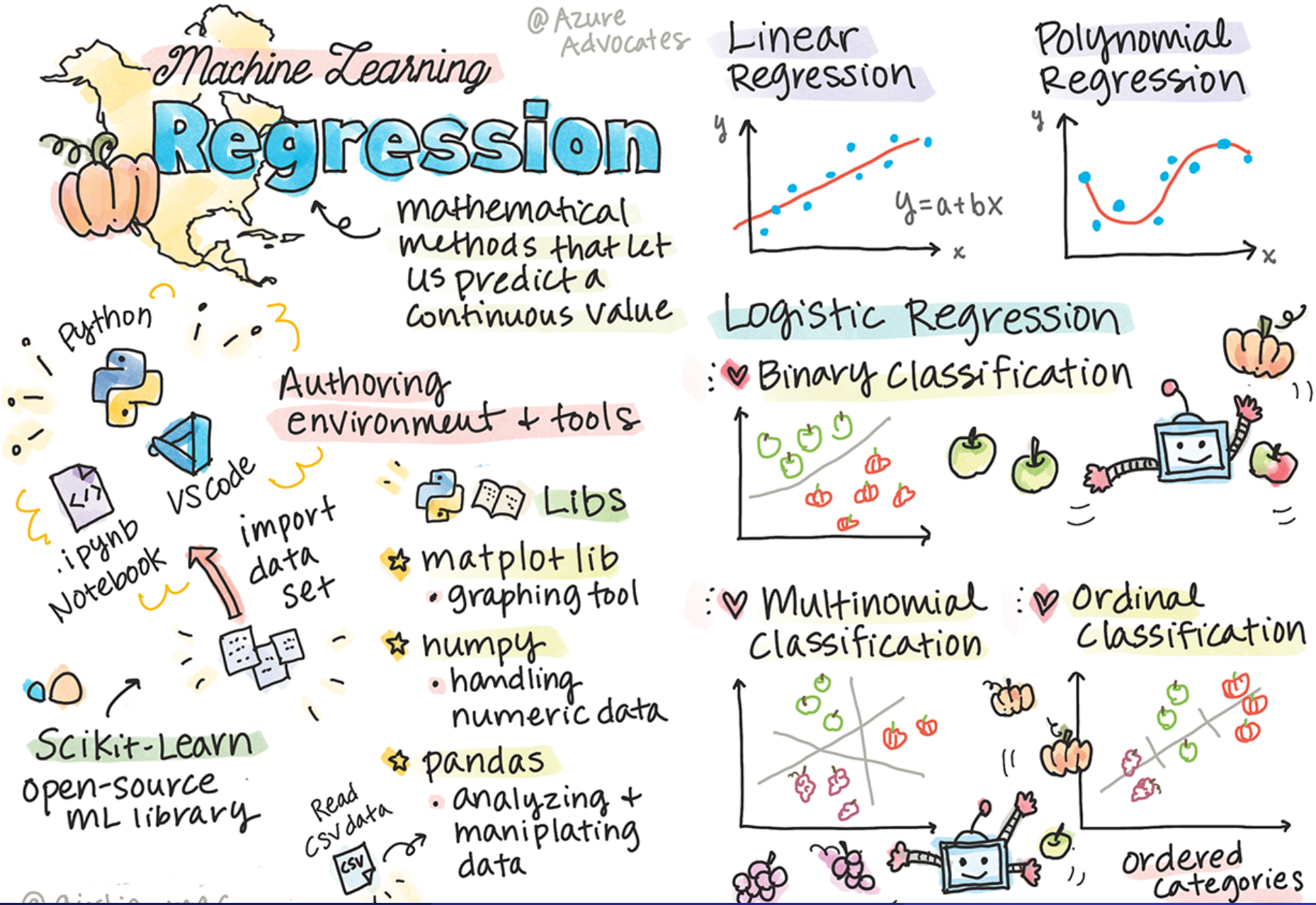
- Input dataset: Matrix of size M times N
  - M = number of samples (row)
  - N = number of features (column)
- Feature: Measurable property of input, e.g. height, weight, age
- Output labels Y: Vector of size M

Two Main ML Problems

1. **Classification**
   - Classify input object into 2+ classes
   - Example: Is this email spam or not?
   - Example: Recognize handwritten digits (0-9)
2. **Regression**
   - Predict a numerical number
   - Example: Predict house prices
   - Example: Forecast temperature

Our Focus: ML and Neural network models for both problems

Regression

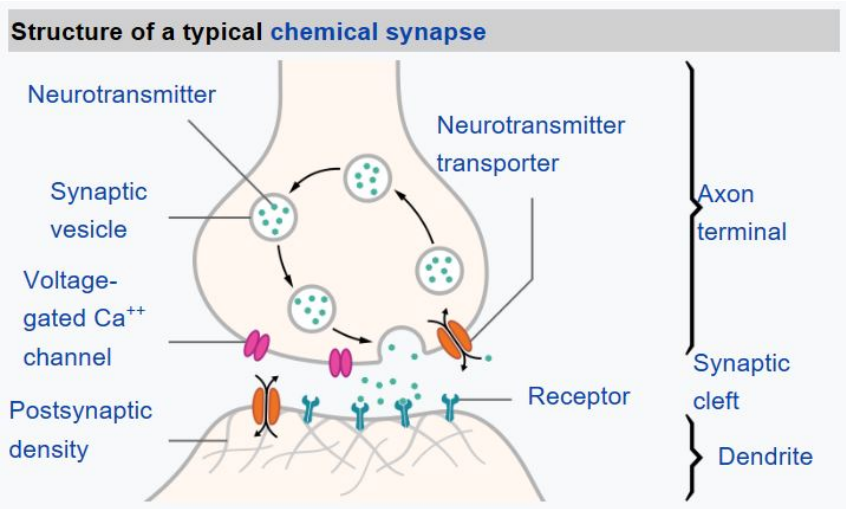

@Azure Advocates
Machine Learning
Regression
mathematical methods that let us predict a continuous value
Linear Regression
y
x
y=a+bx
Polynomial Regression
y
x
Logistic Regression
Binary classification
Multinomial Classification
Ordinal Classification
ordered categories
Python
Authoring environment + tools
VS code
.ipynb Notebook
import data set
Libs
matplot lib
• graphing tool
numpy
• handling numeric data
pandas
• analyzing + maniplating data
Read CSV data
CSV
Scikit-Learn
open-source ML library

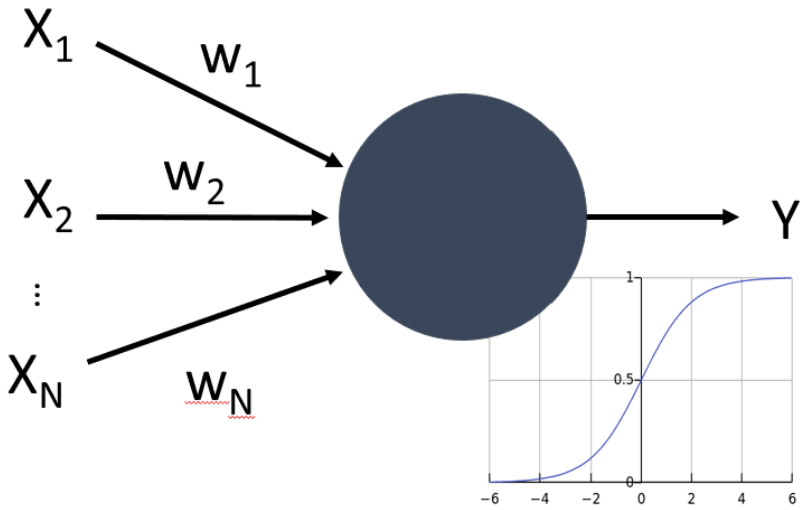
Biological Inspiration

The Human Brain:

- Consists of neural cells (neurons)
- Multiple "inputs": **dendrites**
- Single "output": **axon**
- Connections: **synapses**
  - Varying degrees of conductivity
  - Regulated by neurotransmitters
- Both dendrites and axons conduct electrical signals

Real vs. Artificial Neuron





Left: Real Neuron (Image from Wikipedia)

Right: Artificial Neuron (Simplified mathematical model)

Mathematical Model of a Neuron

Components:

- Multiple inputs: X1, X2, . . . , XN
- Single output: Y
- Series of weights: W1, W2, . . . , WN
- Activation function: f

Output Calculation:

$$Y = f\left(\sum_{i=1}^{N} X_i \cdot W_i\right)$$

Y = f(sum of Xi * Wi for all i)

The Neuron Formula

Mathematical Expression:

- Weighted sum of inputs
- Applied non-linear activation function

Why Non-linear?

- Enables learning complex patterns
- Linear functions too simple for real-world problems
- Biological neurons also non-linear

Historical Foundation

Early Research (1943):

- Warren McCulloch and Walter Pitts
- Paper: "A logical calculus of the ideas immanent in nervous activity"
- First mathematical model of neurons

Learning Theory (1949):

- Donald Hebb
- Book: "The Organization of Behavior: A Neuropsychological Theory"
- Proposed how networks can be trained
- **Hebbian Learning**: "Cells that fire together, wire together"

Course Structure

Topics Covered:

1. **Perceptron**
   - One of the earliest neural network models
   - Two-class classification
2. **Multi-layered Networks**
   - Building our own framework
   - Understanding deep architecture

Course Structure (continued)

Topics Covered:

3. **ML and Neural Network Frameworks**
   - ML: Scikit-learn
   - NN: PyTorch
4. **Overfitting**
   - Common problem in neural networks
   - Prevention techniques
   - Regularization methods

Section 1: Perceptron

What is a Perceptron?

- Earliest neural network model
- Binary classification
- Single-layer architecture
- Foundation for modern neural networks

Learn more: See Perceptron README

Going Deeper:

- Multiple layers of neurons
- Hidden layers
- Building blocks of deep learning

Hands-on Practice:

- Code MLP Using SciKit-Learn for diabetes dataset
- Understand backpropagation
- See how training works internally

Section 4: Overfitting

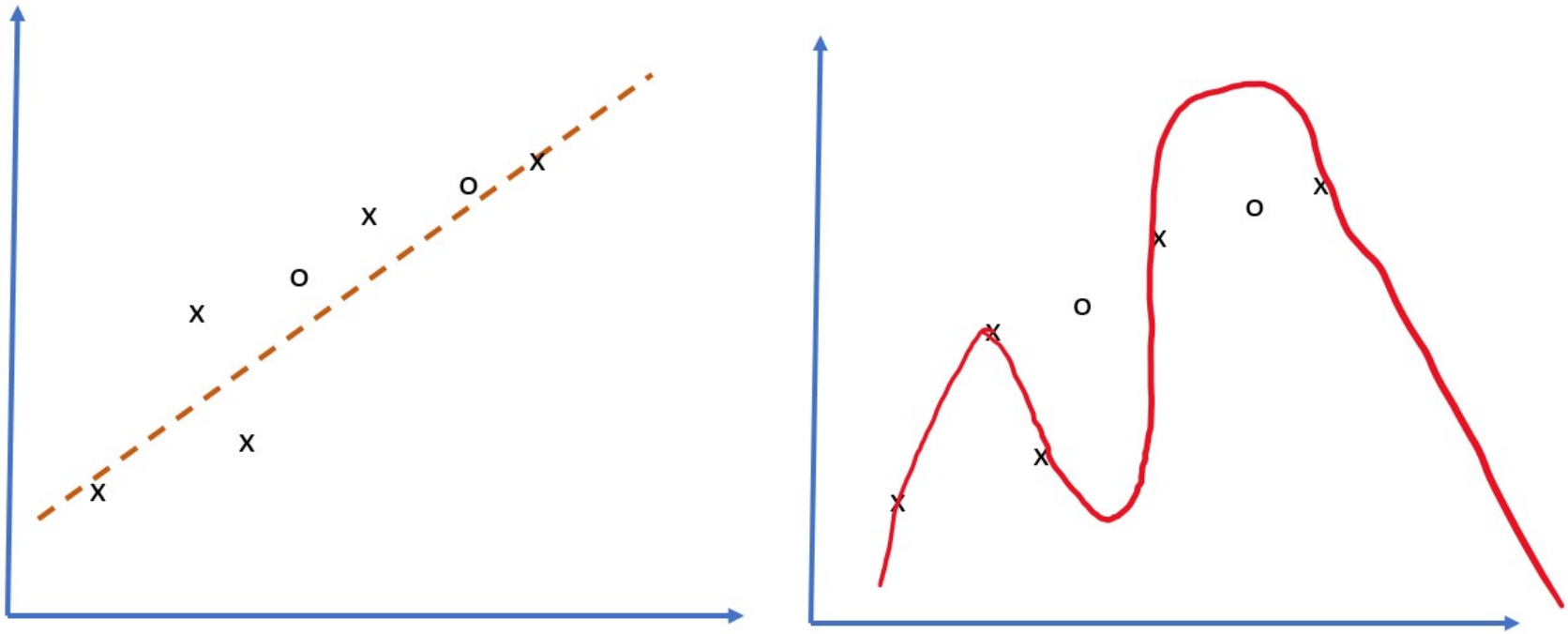
What is Overfitting?

- Model learns training data too well
- Poor generalization to new data
- Memorization vs. learning

Prevention Techniques:

- Regularization (L1, L2)
- Dropout
- Early stopping
- Data augmentation
- Cross-validation

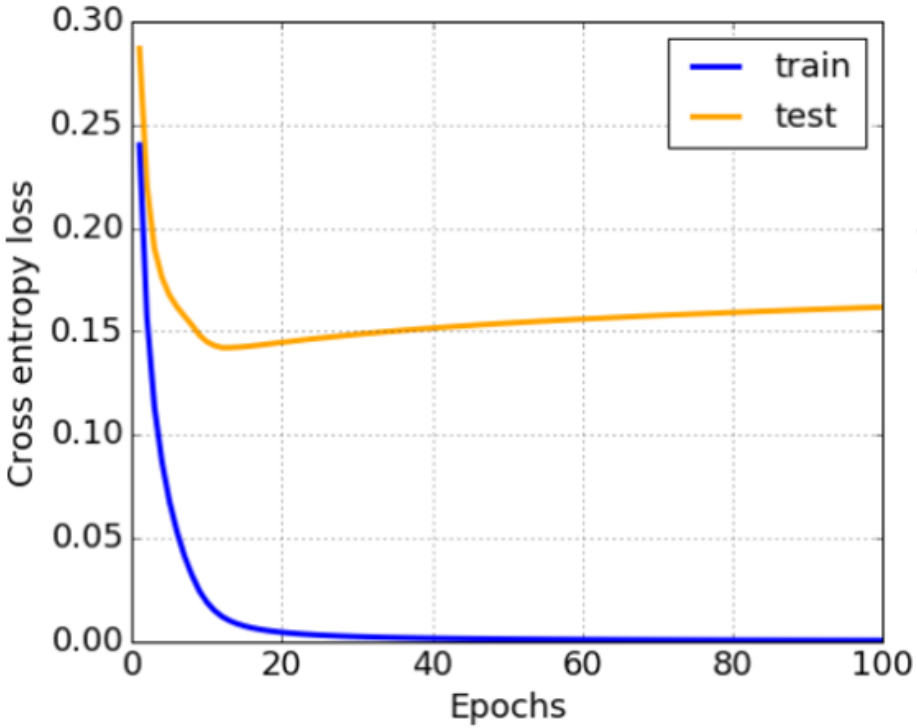
Overfitting Visualization

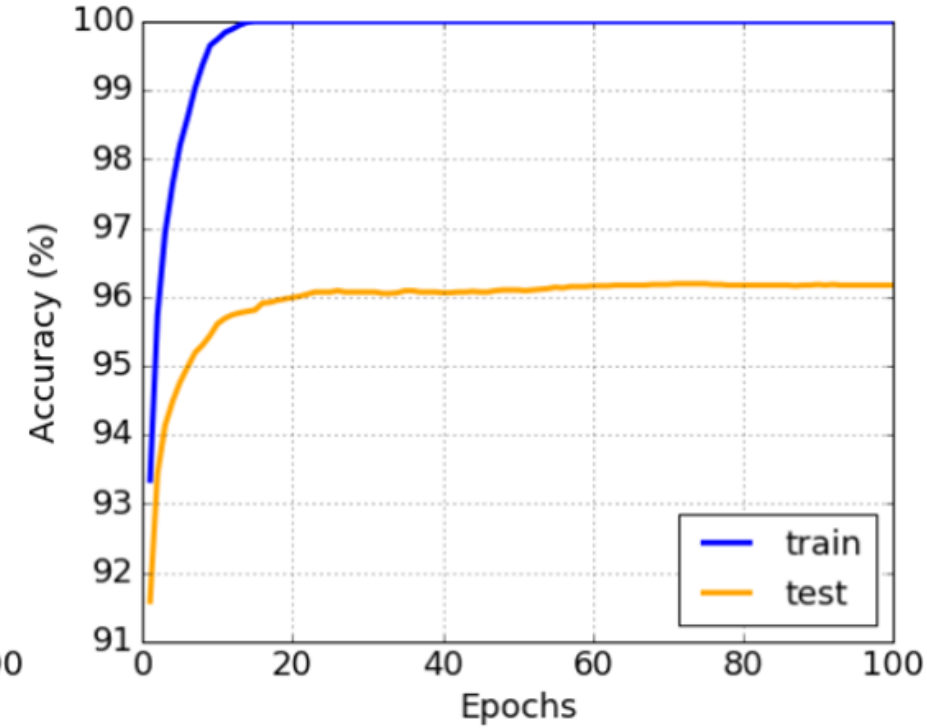


Signs of Overfitting:

- Training accuracy: Very high
- Validation accuracy: Much lower
- Model too complex for the data

Overfitting Diagram





Three Scenarios:

- **Underfitting**: Too simple, misses patterns
- **Good fit**: Captures patterns, generalizes well
- **Overfitting**: Too complex, captures noise

Key Concepts Summary

Neural Networks:

- Mathematical models inspired by the brain
- Consist of interconnected artificial neurons
- Learn from data through training

Core Components:

- Inputs with weights
- Activation functions
- Multiple layers
- Backpropagation for training

Learning Objectives

By the end of this section, you will:

1. Understand neuron mathematical models
2. Build neural networks from scratch
3. Use industry-standard frameworks
4. Recognize and prevent overfitting
5. Apply neural networks to real problems

Why Neural Networks?

Advantages:

- Learn complex non-linear patterns
- Automatic feature extraction
- Scalable to large datasets
- State-of-the-art in many domains

Applications:

- Image recognition
- Natural language processing
- Speech recognition
- Game playing (AlphaGo)
- Autonomous vehicles

Getting Started

Prerequisites:

- Basic Python programming
- Linear algebra fundamentals
- Understanding of calculus (derivatives)
- Familiarity with NumPy

Tools Needed:

- Python 3.x
- VSCode and/or Jupyter Notebook
- PyTorch
- Scikit-learn
- NumPy, Matplotlib
- SHAP: Explainable AI
- Nkululeko: Audio AI

From Perceptron to Deep Learning

Evolution of Neural Networks:

- 1943: Mathematical model (McCulloch-Pitts)
- 1958: Perceptron (Rosenblatt)
- 1969: Limitations discovered (Minsky & Papert)
- 1986: Backpropagation (Rumelhart et al.)
- 2006: Deep Learning renaissance (Hinton)
- 2012+: Modern deep learning era

Training Neural Networks

The Learning Process:

1. **Initialize** weights randomly
2. **Forward pass**: Compute predictions
3. **Calculate loss**: Measure error
4. **Backward pass**: Compute gradients
5. **Update weights**: Gradient descent
6. **Repeat** until convergence

Activation Functions

Common Functions:

- **Sigmoid**: $\sigma(x) = \frac{1}{1+e^{-x}}$
  - Output: (0, 1)
  - Used in binary classification
- **ReLU**: f(x) = max(0, x)
  - Most popular in hidden layers
  - Solves vanishing gradient problem
- **Softmax**: For multi-class classification
  - Outputs probability distribution

Neural Network Architectures

Types of Networks:

- **Feedforward**: Data flows in one direction
- **Convolutional (CNN)**: For images
- **Recurrent (RNN)**: For sequences
- **Transformer**: For language tasks
- **Generative Adversarial (GAN)**: For generation

This Section: Focus on feedforward networks

Practical Considerations

Model Design:

- Number of layers
- Number of neurons per layer
- Choice of activation functions
- Learning rate selection

Training Tips:

- Batch size selection
- Number of epochs
- Monitoring validation loss
- Using callbacks

Common Challenges

Training Issues:

- Vanishing/exploding gradients
- Overfitting (memorization)
- Underfitting (too simple)
- Slow convergence
- Getting stuck in local minima

Solutions:

- Proper initialization
- Batch normalization
- Regularization
- Learning rate scheduling
- Early stopping

The Perceptron: Historical Background

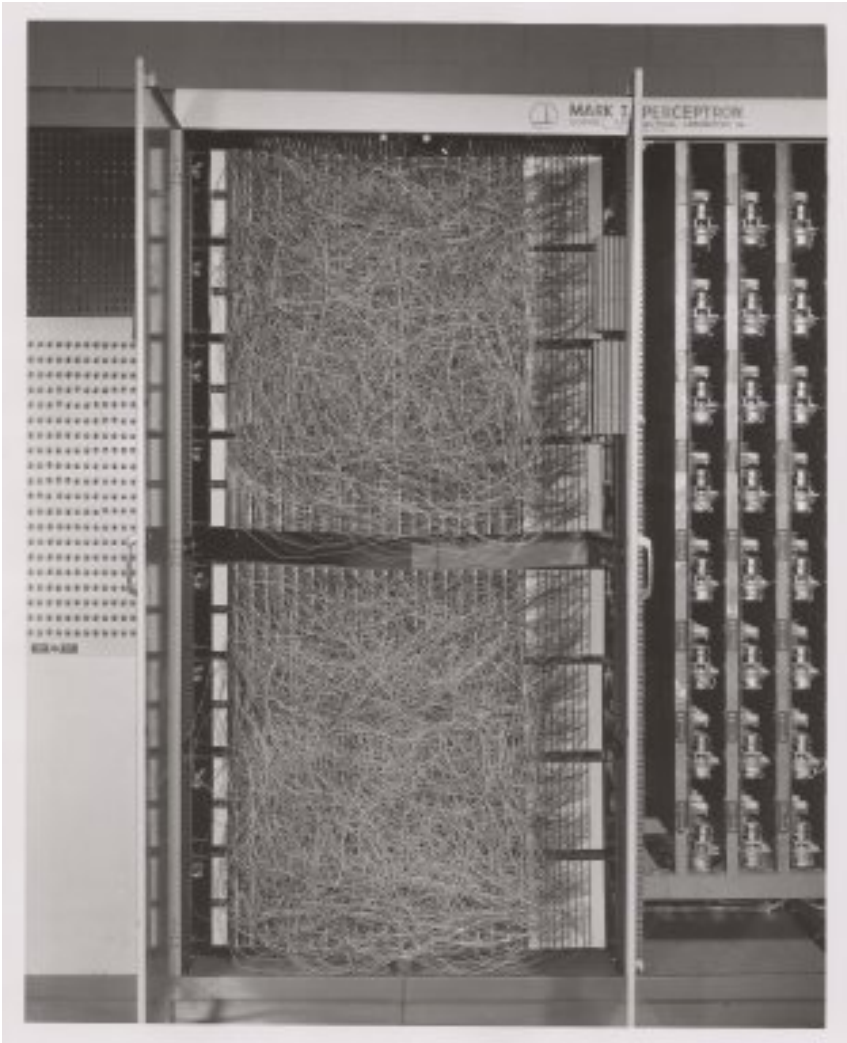
Frank Rosenblatt (1957)

- Cornell Aeronautical Laboratory
- First hardware implementation: "Mark-1"
- Designed to recognize primitive geometric figures
- Triangles, squares, and circles

Input Representation:

- 20x20 photocell array
- 400 inputs
- One binary output

The Mark-1 Perceptron



Images from Wikipedia

Mark-1 Architecture

Simple Neural Network:

- Single neuron (threshold logic unit)
- Neural network weights as potentiometers
- Manual adjustment during training phase

Potentiometer: Device allowing user to adjust circuit resistance

Contemporary Expectations

The New York Times wrote:

> *"The embryo of an electronic computer that [the Navy] expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence."*

Reality vs. Expectations:

- Revolutionary for its time
- But had significant limitations
- Led to "AI Winter" in 1969

Perceptron Model

Binary Classification Model

- Distinguishes between two classes
- Input vector: x (size N features)
- Output: +1 or -1

Output Formula:

$$y(x) = f(w^T x)$$

where f is a step activation function

Step Activation Function

Function Definition:

$$f(x) = \begin{cases} +1 & \text{if } x \geq 0 \\ -1 & \text{if } x < 0 \end{cases}$$

Characteristics:

- Binary output
- Sharp threshold at zero
- Non-differentiable (causes training challenges)

Training the Perceptron

Goal: Find weights vector w that:

- Classifies most values correctly
- Results in the smallest error

Perceptron Criterion:

$$E(w) = -\sum(w^T x_i t_i)$$

where:

- Sum taken on misclassified training points
- x_i = input data
- t_i = -1 or +1 (target labels)

Gradient Descent

Optimization Method:

Start with initial weights $w^{(0)}$

Update at each step:

$$w^{(t+1)} = w^{(t)} - \eta \cdot \nabla E(w)$$

where:

- η = learning rate
- $\nabla E(w)$ = gradient of error

Final Update Rule:

$$w^{(t+1)} = w^{(t)} + \sum(\eta \cdot x_i \cdot t_i)$$

Training Algorithm Components

Key Elements:

- **Learning Rate (eta):** Controls step size
- **Gradient:** Direction of steepest descent
- **Weight Update:** Adjust based on errors
- **Iteration:** Repeat until convergence

Process:

1. Initialize weights
2. Compute output
3. Calculate error
4. Update weights
5. Repeat

Python Implementation

```
def train(positive_examples, negative_examples,
          num_iterations = 100, eta = 1):

    weights = [0,0,0] # Initialize weights

    for i in range(num_iterations):
        pos = random.choice(positive_examples)
        neg = random.choice(negative_examples)

        z = np.dot(pos, weights)
        if z < 0: # positive misclassified
            weights = weights + eta*weights.shape

        z = np.dot(neg, weights)
        if z >= 0: # negative misclassified
            weights = weights - eta*weights.shape
```

Training Process Explained

Step-by-Step:

1. **Initialize:** Random or zero weights
2. **Select Samples:** Pick positive and negative examples
3. **Compute Output:** Calculate $z = w^T x$
4. **Check Classification:**
   - If positive classified as negative: increase weights
   - If negative classified as positive: decrease weights
5. **Iterate:** Repeat for num_iterations

Learning Rate Selection

eta (Learning Rate):

- **Too Large:**
  - Overshooting optimal weights
  - Oscillation, no convergence
- **Too Small:**
  - Slow convergence
  - Many iterations needed
- **Just Right:**
  - Steady progress
  - Efficient convergence

Typical Range: 0.001 to 0.1

Perceptron Limitations

Discovered by Minsky & Papert (1969):

Cannot solve XOR problem:

- Non-linearly separable data
- Need multiple layers
- Led to first "AI Winter"

Other Limitations:

- Only linear decision boundaries
- Sensitive to outliers
- No probabilistic outputs
- Single layer architecture

XOR Problem Illustration

Truth Table:

X1	X2	XOR
0	0	0
0	1	1
1	0	1
1	1	0

Problem: Cannot draw single straight line to separate classes

Solution: Multi-layer perceptron (MLP)

When Perceptrons Work Well

Linearly Separable Problems:

- Binary classification
- Simple pattern recognition
- Text classification (bag of words)
- Spam detection
- Simple geometric shapes

Advantages:

- Fast training
- Simple to implement
- Interpretable weights
- Foundation for understanding deep learning

From Perceptron to Modern Networks

Evolution:

1. **1958:** Single-layer perceptron
2. **1969:** Limitations discovered
3. **1986:** Multi-layer perceptron + backpropagation
4. **1990s:** Support Vector Machines dominate
5. **2006:** Deep learning renaissance
6. **2012+:** Modern deep neural networks

Multi-Layer Perceptron (MLP)

Solving Perceptron Limitations:

- Add hidden layers
- Use differentiable activation functions
- Backpropagation for training
- Can solve XOR and complex problems

Architecture:

- Input layer
- One or more hidden layers
- Output layer

Practical Applications Today

Where Perceptrons Are Still Used:

1. **Linear Classifiers:**
   - Simple baseline models
   - Feature importance analysis
2. **Ensemble Components:**
   - Part of voting systems
   - Combination with other models
3. **Educational Purposes:**
   - Understanding neural network basics
   - Introduction to gradient descent

Perceptron vs. Modern Networks

Feature	Perceptron	Modern DNNs
Layers	Single	Multiple
Activation	Step	ReLU, Sigmoid, etc.
Training	Simple rule	Backpropagation
Capacity	Linear only	Non-linear
Speed	Very fast	Slower
Applications	Limited	Universal

Key Takeaways - Perceptron

Essential Concepts:

1. First artificial neural network model
2. Binary classification using weighted sum
3. Step activation function
4. Gradient descent training
5. Linear decision boundary limitation
6. Foundation for modern deep learning

Debugging Perceptron Training

Common Issues:

- **Not Converging:**
  - Adjust learning rate
  - Check data separability
  - Increase iterations
- **Poor Performance:**
  - Data not linearly separable
  - Need feature engineering
  - Consider MLP instead

Feature Engineering for Perceptrons

Improving Performance:

- **Polynomial Features:** x, x^2, x^3
- **Interaction Terms:** $x_1 \cdot x_2$
- **Normalization:** Scale features
- **Domain Knowledge:** Create relevant features

Goal: Make data linearly separable

Visualization Techniques

Understanding Perceptron:

1. **Decision Boundary:** Plot separating line
2. **Weight Vector:** Direction of classification
3. **Training Progress:** Error over iterations
4. **Feature Space:** 2D/3D projections

Tools:

- Matplotlib for plotting
- Seaborn for visualization
- Interactive plots with Plotly

Perceptron Convergence Theorem

Theoretical Guarantee:

If data is linearly separable:

- Perceptron will converge
- Finite number of iterations
- Find perfect separator

Conditions:

- Data must be linearly separable
- Finite dataset
- Proper learning rate

Modern Variants

Extensions and Improvements:

1. **Voted Perceptron:**
   - Multiple weight vectors
   - Voting scheme
2. **Averaged Perceptron:**
   - Average all weight vectors
   - Better generalization
3. **Kernel Perceptron:**
   - Non-linear decision boundaries
   - Kernel trick application

Summary and Conclusion

Perceptron Legacy:

- Historical significance in AI
- Foundation of neural networks
- Still relevant for education
- Simple yet powerful concept

Next Steps:

- Multi-layer networks
- Backpropagation
- Modern frameworks (PyTorch, TensorFlow)

Final Thoughts

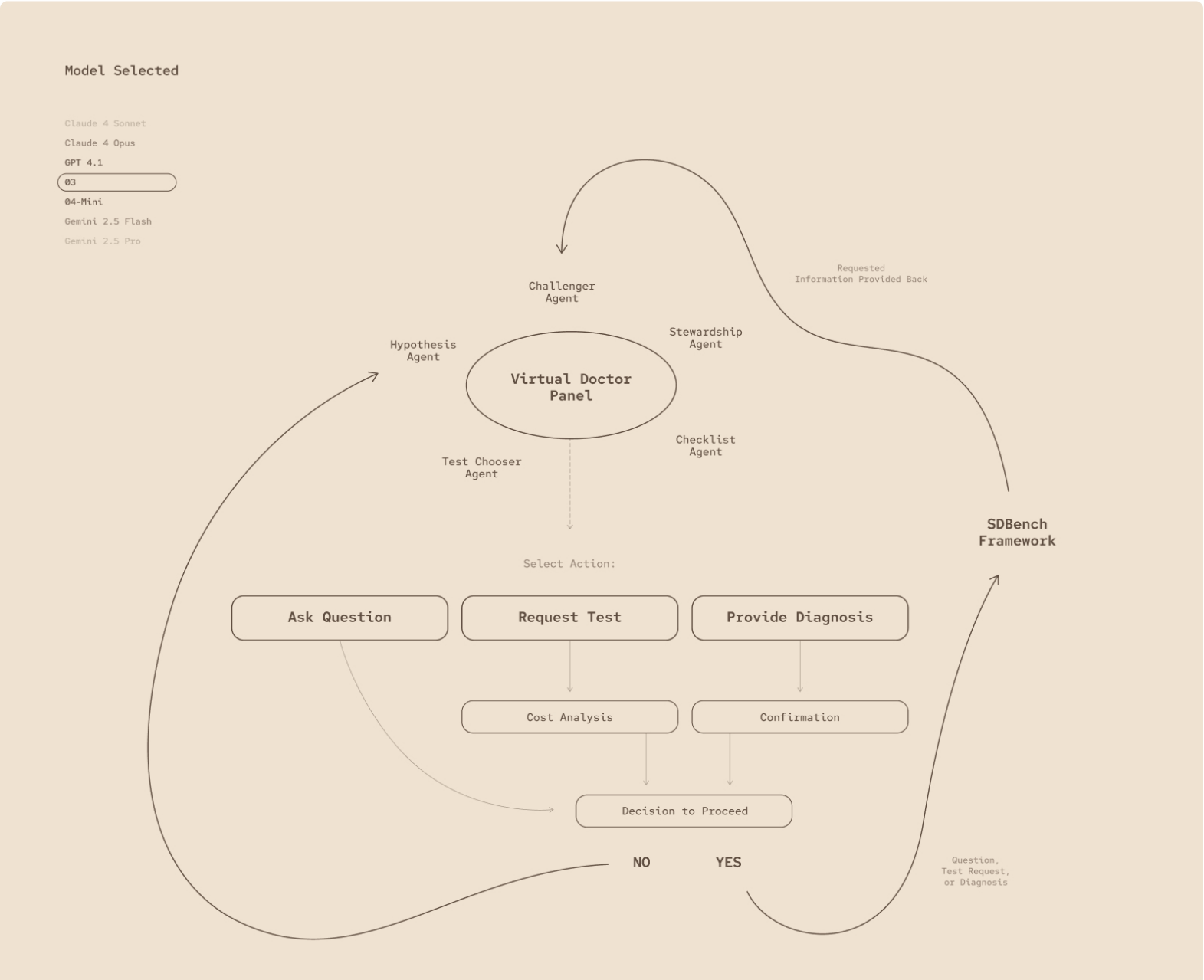
Why Study AI and ML?

1. Understand the foundations of modern AI
2. Grasp both symbolic and neural approaches
3. Appreciate deep learning evolution
4. Build intuition for complex models

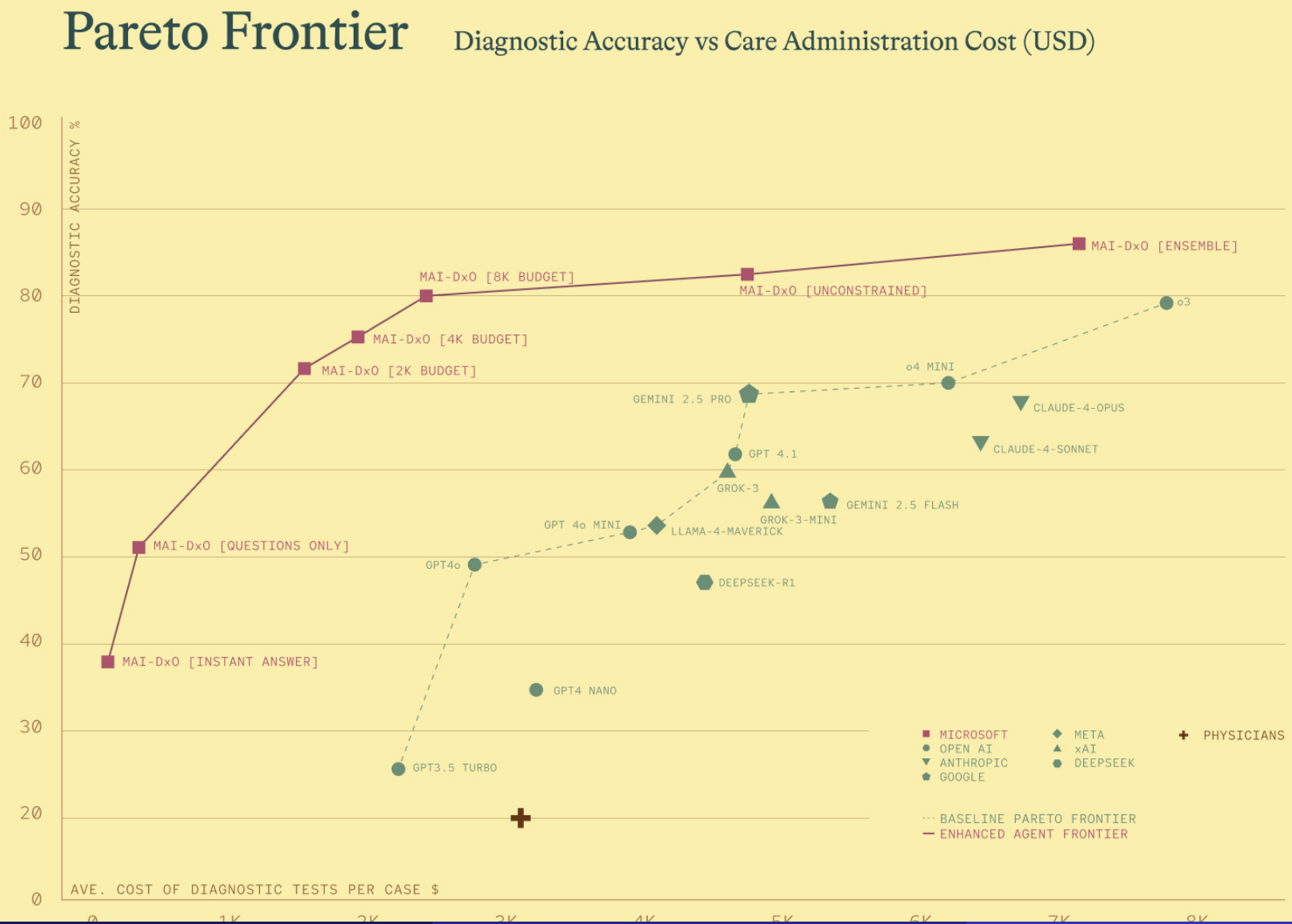
Remember:

- AI is diverse: symbolic reasoning AND neural networks
- Every deep network is built on fundamental principles
- Simple models teach important lessons
- Start simple, scale complexity gradually

AI for Healthcare: virtual doctor



Pareto Frontier: Diagnostic Accuracy



Discussion and Quiz

Part 1 AI:

- Pre-lecture quiz: (https://ff-quizzes.netlify.app/en/ai/quiz/1)[https://ff-quizzes.netlify.app/en/ai/quiz/1]
- Post-lecture quiz: (https://ff-quizzes.netlify.app/en/ai/quiz/2)[https://ff-quizzes.netlify.app/en/ai/quiz/2]

Part 2 Perceptron:

- Pre-lecture quiz: (https://ff-quizzes.netlify.app/en/ai/quiz/3)[https://ff-quizzes.netlify.app/en/ai/quiz/3]
- Post-lecture quiz: (https://ff-quizzes.netlify.app/en/ai/quiz/4)[https://ff-quizzes.netlify.app/en/ai/quiz/4]

ML Resources: