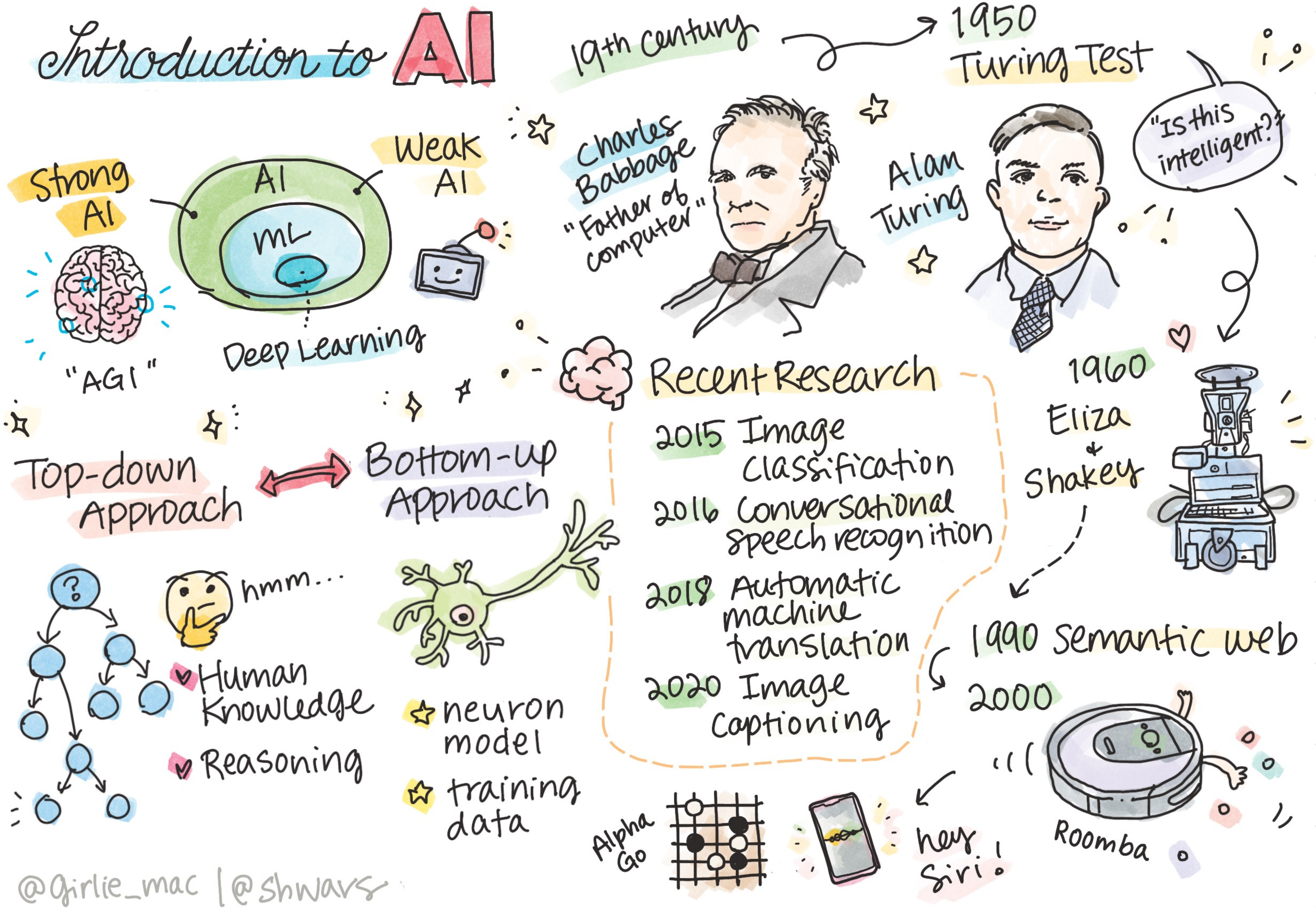
Artificial Intelligence (AI)

Introduction



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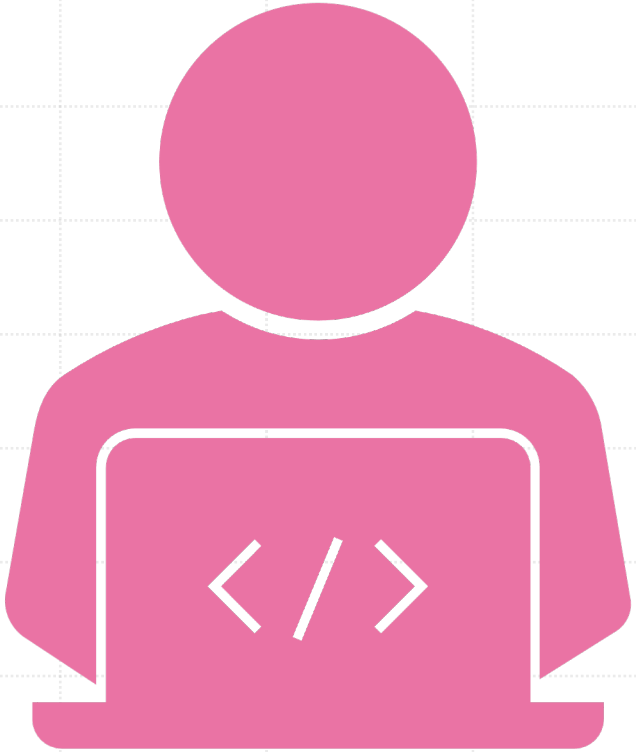
Artificial Intelligence

AI studies how to make computers exhibit intelligent behavior.

Focuses on tasks that humans are naturally good at.

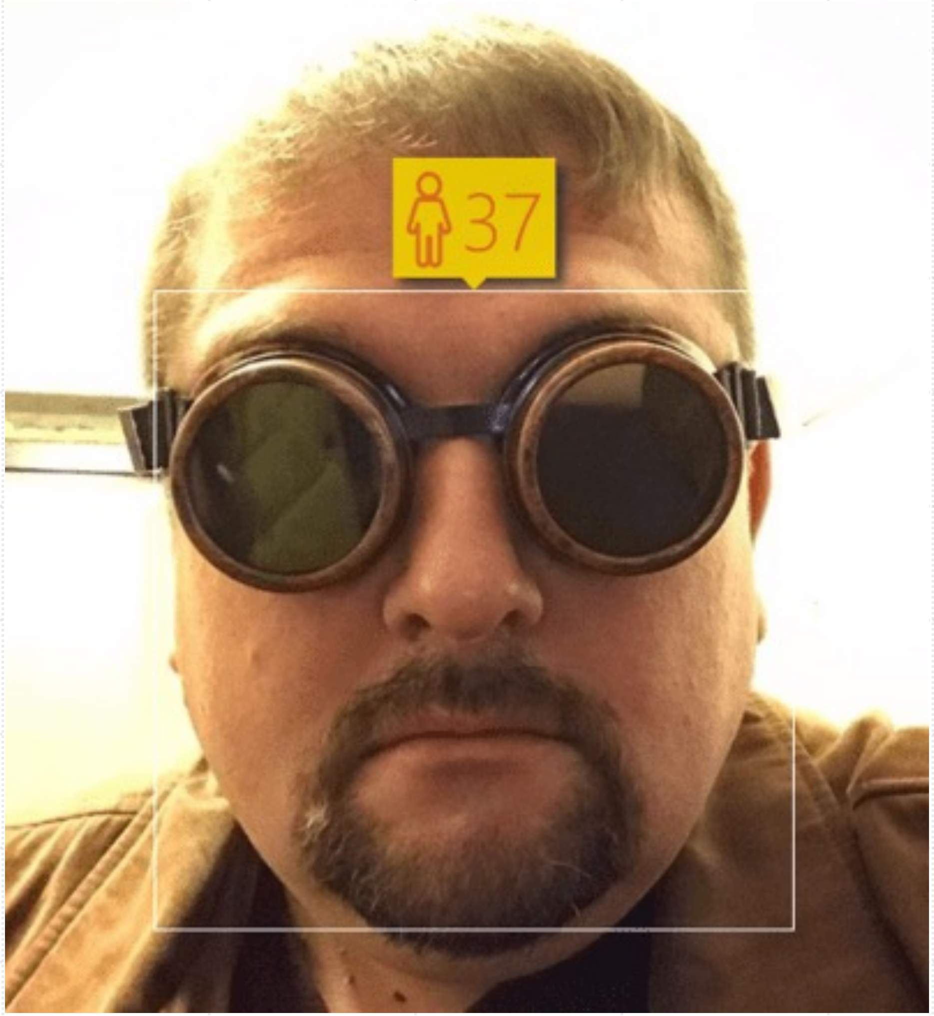
Historical Background

- Inception with Charles Babbage's computers designed for numerical operations.
- Modern computers: Evolved but still based on Babbage's concept of algorithm-based operations.



Core Concept of AI

- Modern challenges: Tasks without explicit solutions or well-defined procedures.
- Example: Estimating a person's age from a photograph.
  - Humans learn this through experience, but can't easily articulate the process.
  - AI aims to enable computers to perform such intuitive tasks.



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Weak AI vs. Strong AI

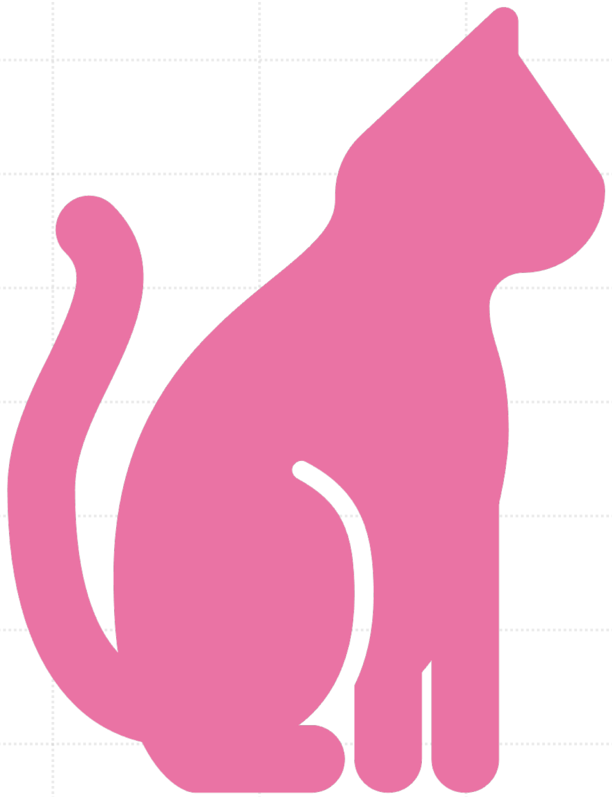
Weak AI	Strong AI
Weak AI refers to AI systems that are designed and trained for a specific task or a narrow set of tasks.	Strong AI, or Artificial General Intelligence (AGI), refers to AI systems with human-level intelligence and understanding.
These AI systems are not generally intelligent; they excel in performing a predefined task but lack true understanding or consciousness.	These AI systems have the ability to perform any intellectual task that a human being can do, adapt to different domains, and possess a form of consciousness or self-awareness.
Examples of weak AI include virtual assistants like Siri or Alexa, recommendation algorithms used by streaming services, and chatbots that are designed for specific customer service tasks.	Achieving Strong AI is a long-term goal of AI research and would require the development of AI systems that can reason, learn, understand, and adapt across a wide range of tasks and contexts.
Weak AI is highly specialized and does not possess human-like cognitive abilities or general problem-solving capabilities beyond its narrow domain.	Strong AI is currently a theoretical concept, and no AI system has reached this level of general intelligence

Ambiguity in Defining Intelligence

- Lack of a clear, universal definition of "intelligence."
- Associated with concepts like abstract thinking and self-awareness, but not definitively.

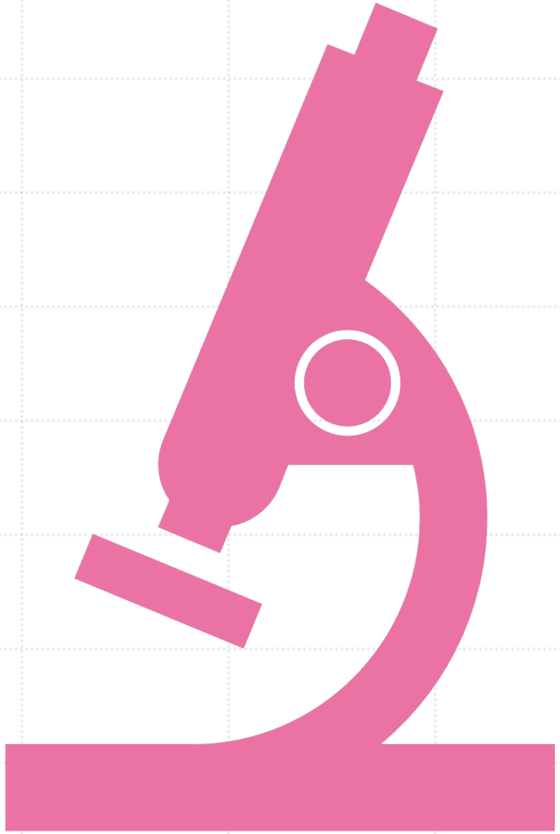
Illustrating Ambiguity with an Example

- Question: "Is a cat intelligent?"
  - Varies in interpretation and response among individuals.
  - Highlights the subjective nature of defining intelligence.



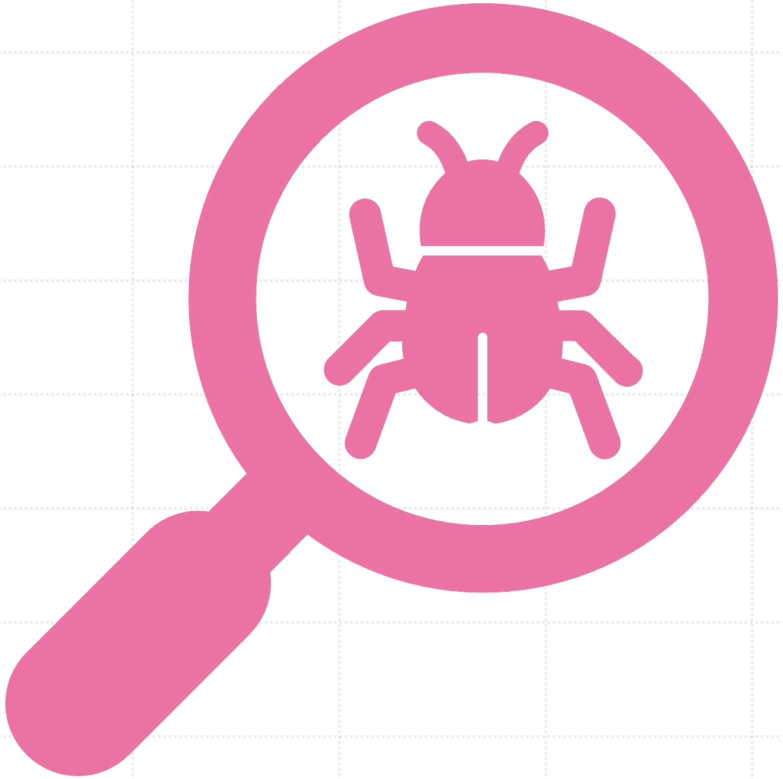
Challenges in Measuring Intelligence

- No universally accepted test to conclusively determine intelligence.
- The impracticality of traditional measures, like an IQ test, for non-human subjects (e.g., cats).



Concept of AGI and Turing Test

- AGI (Artificial General Intelligence) requires a benchmark for "true intelligence."
- Alan Turing's proposal: Turing Test as a criterion for intelligence.



Turing Test Explained

- Involves comparing a system's responses to that of a human in text-based dialogue.
- A human interrogator assesses the indistinguishability of the system from a real person.
- If the interrogator can't tell the difference, the system is considered intelligent.

Case Study: Eugene Goostman Chat-bot

- Developed in St. Petersburg, it nearly passed the Turing Test in 2014.
- Presented as a 13-year-old Ukrainian boy, explaining any knowledge gaps or textual discrepancies.
- Managed to convince 30% of judges of its human identity in a 5-minute conversation.

Critical Perspective on Turing Test and Intelligence

- Turing predicted machines would pass this test by 2000.
- Success in the Turing Test doesn't necessarily equate to actual intelligence.
- The creators' ingenuity, not the system's intelligence, can influence the test outcome.

Modeling Human Intelligence in Computers

Goal: Replicate human thinking patterns in computer systems.

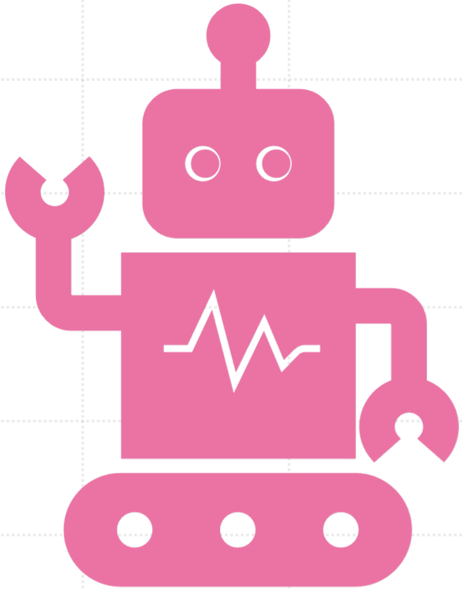
Understanding human intelligence is key to programming artificial intelligence.

Understanding Decision-Making Processes

- Investigating how humans make decisions is crucial.
- Recognition of the coexistence of subconscious and conscious processes.

Examples of Human Cognitive Processes

- Subconscious processing: Instantly distinguishing a cat from a dog without active thought.
- Conscious reasoning: Engaging in deliberate thought for complex decision-making.



Different Approaches to AI

Top-down Approach (Symbolic Reasoning)

A top-down approach models the way a person reasons to solve a problem. It involves extracting **knowledge** from a human being, and representing it in a computer-readable form. We also need to develop a way to model **reasoning** inside a computer.

Bottom-up Approach (Neural Networks)

A bottom-up approach models the structure of a human brain, consisting of huge number of simple units called **neurons**. Each neuron acts like a weighted average of its inputs, and we can train a network of neurons to solve useful problems by providing **training data**.

Alternative Approaches to Intelligence

Emergent, Synergetic, and Multi-Agent Approach

- Complex intelligent behavior arises from interactions of numerous simple agents.
- Evolutionary cybernetics: Intelligence emerges from simpler, reactive behaviors.
- Concept of metasystem transition: Progressive integration of simple systems into complex ones.

Evolutionary Approach: Genetic Algorithms

- Optimization process inspired by biological evolution principles.
- Involves selection, mutation, and inheritance to evolve solutions to problems.

Top-Down Approach in AI

Focuses on modeling human reasoning and thought processes.

Known as symbolic reasoning: formalizing thought processes for programming.

Involves rule-based decision making.

Example: Doctors use symptoms (like fever) and rules to diagnose.

Challenges:

Relies on precise knowledge representation and reasoning.

Difficulty in extracting implicit knowledge from experts (e.g., a doctor's intuitive

Bottom-Up Approach in AI

Aims to replicate the brain's basic elements, like neurons.

Utilizes artificial neural networks to mimic learning processes.

Learning through examples and observations, akin to a child's learning.

Effective in tasks where explicit rules are hard to define.

A Brief History of AI

Early History of AI

Began in the mid-20th century.

Initial focus on symbolic reasoning.

Symbolic Reasoning and Its Impact

Led to creation of expert systems: programs acting as experts in specific domains.

Achieved significant early successes.

Limitations and Challenges

Scalability issues: Difficulties in extracting and representing expert knowledge.

Maintenance of knowledge bases: Complex and expensive.

These challenges contributed to the AI Winter in the 1970s.

Decline in interest and funding due to practical limitations of early AI approaches.

Brief History of AI

1950

Term "AI"

Chess play as Search

Isaak Asimov, 3 laws of robotics

Turing Test

1960

ELIZA talking bot

Tree Decision Making

Shakey

1970

AI Winter: Critical Feedback

Scruffy vs Neat AI

1980

Expert Systems

Revival of Connectionism

1990

Did we ask too much?

Computer learns to play games – Deep Blue

Semantic Web

2000

Everything needed a Face

iRobot

Google Self-Driving Car

Roomba

2010

IBM Watson wins Jeopardy

Voice Assistants by Google, Apple, Microsoft

> 2014

Eugene Goostman

Human parity in Image Recognition & Voice Recognition

Alpha Go / Alexa

AI: Broken Into sub-fields

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Evolution of AI Over Time

Cheaper computing resources and data abundance enhanced neural network approaches.

Recent AI achievements primarily driven by neural networks.

Chess Programs: An Example of Evolving AI Approaches

Early Programs

Based on search algorithms and move estimation (alpha-beta pruning).

Effective in late-game scenarios with fewer possible moves.

Intermediate Development

Case-based reasoning: Learning from historical human matches.

Improvement for early-game scenarios with vast move possibilities.

Modern Programs

Utilize neural networks and reinforcement learning.

Learn by playing numerous games against themselves, quickly evolving strategies.

Evolution in Dialogue Systems

Early Systems

- Simple grammatical rules for conversation (e.g., Eliza).

Modern Assistants

- Hybrid systems: Neural networks for speech-to-text and intent recognition.
- Reasoning and algorithms for action execution (Cortana, Siri, Google Assistant).

Future Trends

- Potential for fully neural network-based dialogue systems.
- Success of models like GPT and Turing-NLG in natural language processing.

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…

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Recent AI Research

Neural Network Research Growth

- Significant surge around 2010.
- Fueled by the availability of large public datasets.

Role of ImageNet

- A vast collection of about 14 million annotated images.
- Spawned the ImageNet Large Scale Visual Recognition Challenge.
- This challenge significantly advanced the field of computer vision.

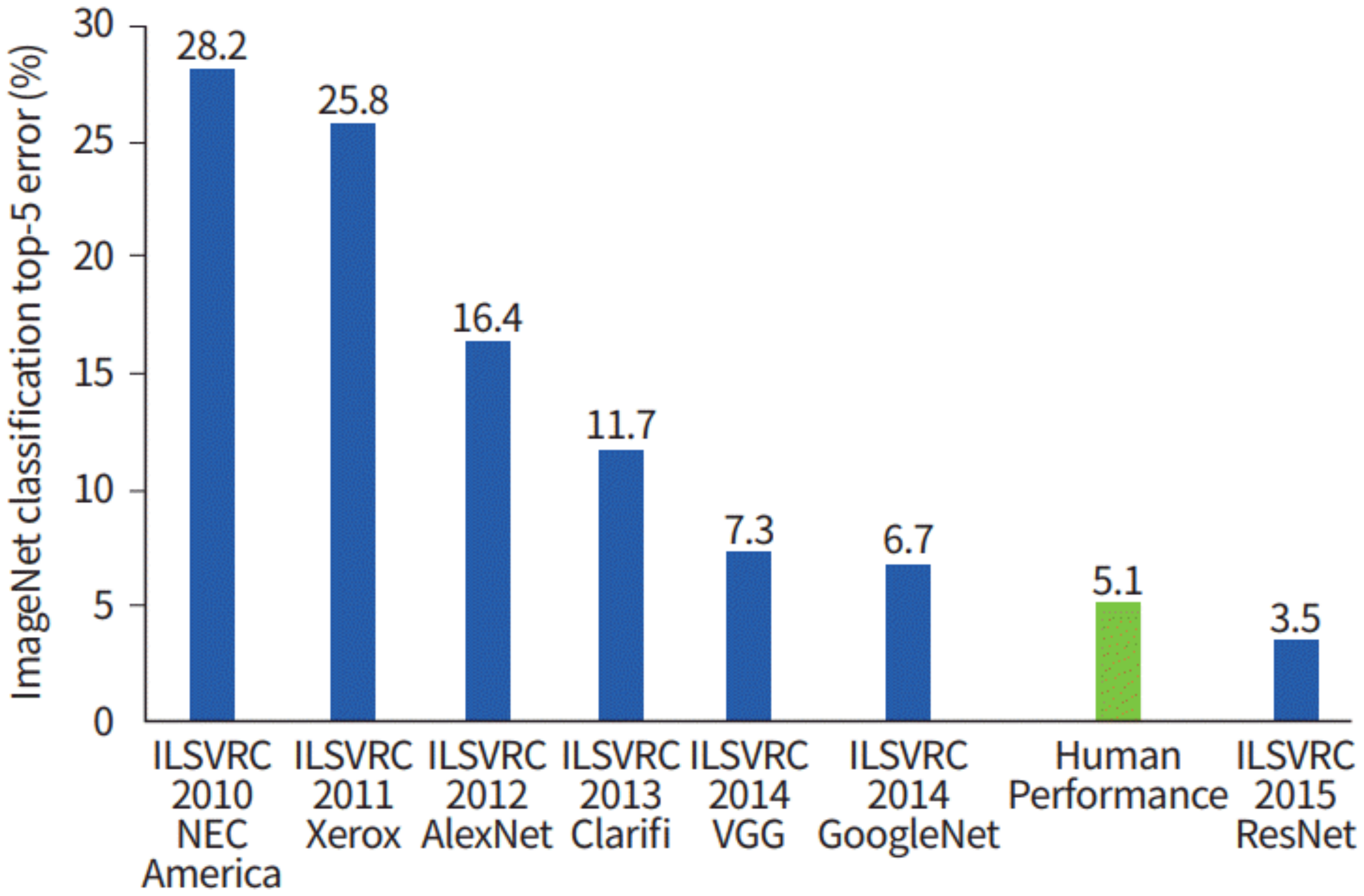

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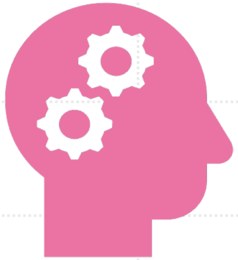
Image classification

Convolutional Neural Networks (CNNs) in Image Classification

Introduced in 2012 for image classification tasks.

Resulted in a dramatic reduction of error rates: from nearly 30% to 16.4%.



Advancement with ResNet Architecture

Developed by Microsoft Research in 2015.

Achieved human-level accuracy in image classification.

ResNet's deep learning architecture was a significant milestone in AI.

Neural Networks demonstrated very successful behaviour in many tasks

Year	Human Parity achieved
2015	Image Classification
2016	Conversational Speech Recognition
2018	Automatic Machine Translation (Chinese-to-English)
2020	Image Captioning

Natural Language Processing

Advancements in Large Language Models

Significant progress in recent years with models like BERT and GPT-3.

Key Factors for Success

Abundance of general text data for training.

Ability to capture the structure and meaning of texts effectively.

Training and Specialization Approach

Pre-training on vast, general text collections.

Subsequent specialization for specific tasks and applications.