Artificial Intelligence
An Introduction[1]

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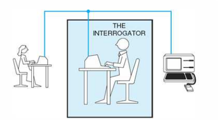
[1] The primary source of these notes are the slides of Professor Hwee Tou Ng from Singapore. I sincerely thank him for this.

History of AI

- Leibniz, Babbage, Boole, Frege, Russell, Tarski ...
- Turing (1930's)
  - Turing Machine (TM)
  - **Turing Test** "Operationalizing" Intelligence
    - Machine's ability to demonstrate intelligence
    - Human Judge "converses" with human and machine
    - BOTH try to appear human
    - All participants are placed in isolated locations
    - If Judge cannot reliably tell the machine from the human, the machine Passes the test
- The Test itself



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  If a problem is not solvable by a TM, it is not solvable by people either

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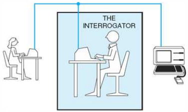

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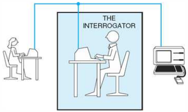

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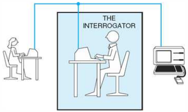

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- 1940s: McCulloch-Pitts, Wiener, Ashby
  - Neuron models
  - Cybernetics - Feedback
  - Teleological behavior
    - Study of design and purpose
    - All things to be designed for or directed toward a final result
    - There is an inherent purpose or final cause for all that exists
  - Homeostat
    - Device built by Ashby in 1948
    - Adaptive ultrastable system from four bomb control units
    - Had inputs and feedback
    - Used magnetically-driven water-filled potentiometers
    - Stabilizes effects of disturbances introduced into the system
    - *Time*: "Closest thing to a synthetic brain... designed by man"

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  - Machina Speculatrix (Elmer 1948, and Elsie 1949)
    - First electronic autonomous robots
    - Rich connections between a small number of brain cells - Very complex behaviors
    - Described as tortoises due to their shape and slow motion
    - "Taught us" about the secrets of organization and life
    - Three-wheeled tortoise robots
    - Could find their way to a recharging station
  - Self-reproducing automata
    - Self-replication: Process by which a thing copies of itself
    - Self-reproductive systems:Produce copies of themselves
    - Primitives: From metal bar and wire
    - Self-assembling systems
    - Assemble copies of themselves from finished parts
    - Self-reproducing "computer programs"

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History of AI: 1950's

- 1950s: Simon, Newell, McCarthy, Minsky: "AI" (1956)
  - Fundamentals of Classification
  - Neural networks
  - Perceptron

History of AI: Since 1960's

- 1960s: Lisp, Adaline, Fuzzy sets (Zadeh 65)
- 1960s: General Problem Solver (GPS), Logic Theory
- 1970s: Backpropogation, Fuzzy Controllers
- 1970s: Knowledge Engineering, Genetic Algorithms (GA)
- 1970s: Production systems, Expert systems
- 1970s: Natural Language Processing (NLP)
- SHRDLU
  - SHRDLU was an early NLP developed by Winograd at MIT
  - Micro Planner and Lisp programming language on a PDP-6
  - SHRDLU was derived from ETAOIN SHRDLU
  - Arrangement of the alpha keys on a Linotype machine in descending frequency order

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History of AI: 1970's & 1980's

- 1970s: Theorem proving, Planning
- 1980s: NN / Connectionist boom, Boltzmann Machine
- 1980s: Knowledge Representation (KR)
- 1980s: More semantics in NLP (Conceptual Dependency)
- 1980s: Symbolic Machine Learning (ML)

History of AI: Since 1990's

- More NN
- Subsumption Architecture (Brooks)
  - Decompose complicated intelligent behaviour
  - Many "simple" behaviour modules organized into layers
  - Each layer implements a particular goal
  - Higher layers are increasingly abstract
  - A robot's layers:
    - Lowest layer could be "avoid an object"
    - On top of it would be the layer "wander around"
    - Which in turn lies under "explore the world"
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- Reinforcement Learning
- Bayesian Belief Nets
- Data Mining
- More NN, More GA, GP, Artificial-Life
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- "Bottom-up or behavior-based AI" vs "Top-down AI"
- "Emergent Computing", Swarm Intelligence
- Self-Organization...

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What is Intelligence

- Intelligence is:
  - Intellectual (?) behavior that we admire
  - But don’t understand
  - Intelligence is manifested in behavior
  - Closely related to surviving in a complex world
  - Or ...

"2" kinds of AI (or 3 or 4)

- Engineering vs "Cognitive Science"
  - Making usefully smart machines, somehow:
    - Expert systems; Deep Blue; some Data Mining
  - Understanding *how* minds work
    - AI to express and test psychological/linguistic etc. theories

Kinds of AI

- Classical/Top-down / Symbolic vs Behavior-based / Bottom-up / Subsymbolic Mind vs Brain
    - “Physical symbol system hypothesis”
        - Hi-level approach is *brittle*
        - Bottom-up approach often unimpressive
- *Scruffies* vs *Neats*

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Kinds of AI

- Weak AI vs Strong AI
  - Chinese Room argument (John Searle)
  - No such things as AI...
  - An experiment: Someone who knows only English
  - Sits alone in a room following English instructions for manipulating strings of Chinese characters
  - To those outside the room it appears as if someone in the room understands Chinese.
  - Shows that while computers may *appear* to converse in natural language, they cannot – even in principle.
  - Searle argues that computers merely use syntactic rules to manipulate symbol strings
  - Have no understanding of meaning or semantics.

Theoretical insights in AI: Concern tradeoffs

- Tradeoffs: Efficiency and Generality
- Tradeoffs: Robustness and Power
- Tradeoffs: Design complexity - Ability to degrade gracefully
- Tradeoffs: Prior cooking and Achievement
- Tradeoffs: Memory and Inference
- Above All Tradeoffs: Memory and Time

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AI: All about Tradeoffs

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AI must be *Scruffy*...

- Neatness is impossible in complex domains
- Complex domains: Structure that requires solutions
- Found by exploring branching paths in a search space
  - No. of branches is exponential function of path depth
- Any intelligent agent needs to find tricks and shortcuts
- Even in formally specified domains!
- Unless: Infinitely large and fast computers
- Good shortcuts cannot be worked out in advance
- They are not perfect - even in mathematics
- Shortcuts & laziness: Go hand in hand...
- Key to intelligence (Gauss 1..100)

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The *Real World* is even Harder

- Lack of complete initial information
- Range of things to do is large (branching factor!)
- Search spaces are huge
- Things happen fast
- There are deadlines
- Rapidly accessible and executable heuristics
- Must be learned by trial and error (for example)
- Such heuristic rules are bound to be fallible
  - Overgeneralization
  - Poor observations, weak sensors
  - Errors in measurement
  - Inadequate concepts
  - Noise, environmental variance etc...

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Problems with Heuristics

- Rules and facts should be consistent
  - Consistency is undecidable
  - (Approximate) Consistency checking is explosive
  - Maintaining consistency also explosive
- To revise a belief, you need
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  - Allow for finding related beliefs
  - Identifying and retracting underlying assumptions etc.
- A huge reason maintenance system won't do

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Semantics is *Scruffy* too

- Conceptual schemes: Open-ended
- Unlike formal languages
- There is no formal, recursive semantics for NL:
  - We don't know the extension-assigning functions!
- Concepts:
  - May be indeterminate, vague, or ambiguous
  - Prompt conceptual innovations
  - Empirical concepts: No crisp necess./suff. conditions
  - Many concepts are theoretical

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Scruffiness is *Inevitable*

- Scruffiness *Inevitable* for any resource-limited being!
- No practical strategy to reduce scruffiness works always
- AI must be scruffy, for neat reasons
- Thus: Study what the history has come up with
  - Of course: Theories about such inevitably scruffy systems
  - As neat as possible (maximally falsifiable etc.!!)

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By the Way

- Nearly anything you want to compute you can't !!
  - Because there are countably many Turing machines
  - But *Uncountably* many functions
- The interesting things you can compute
  - Too expensive to compute
  - So, you can't compute them
  - Exponential worst case run-time functions
  - $T(n) = kC^n$ e.g. 1 input item takes 10^{-7} sec, n=50, complexity is 2^n : $20 * 10^{13}$ years
- Biological systems must use approximate solutions
  - Learning: On-line regularity detection for prediction
  - Experimentation and mental simulation
- "To be adaptable, an organism must be suboptimal" (Gould)

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Many fields have contributed to AI

- In the form of ideas, viewpoints and techniques
- Philosophy: Logic, reasoning, mind as a physical system
- Mathematics: Formal representation and proofs
- Mathematics: Computation, (un)decidability, (in)tractability
- Mathematics: Probability, fuzzy theory
- Psychology: Learning, perception, motor control
- Economics: Theory of rational decisions, game theory

AI is **Highly** Interdisciplinary

Other fields that have contributed to AI:

- Linguistics: Knowledge representation, grammar
- Neuroscience: Physical substrate for mental activities
- Biology: Adaptation, evolution of complex systems
- Controls: Homeostatic systems, stability, optimal agents
- Complex Systems Theory etc. etc. etc....

- Think like humans
  - Cognitive modelling (AI + Psychology)
- Act like humans
  - Turing test approach: needs NLP, KR, ML, ...
- Think rationally
  - First-Order-Logic based problem solving and planning
  - Closely related to automated theorem proving
- Act rationally
  - A rational agent acts so as to achieve its goals
  - Given its beliefs & limited rationality
- Autonomous agents, robots, evolutionary computation

Some Subareas of AI...

- Heuristic search
  - Problem solving, planning, game playing
- Theorem proving
- Knowledge-based (KB) systems
  - Knowledge Engineering (KE);
  - Knowledge Representation (KR); Expert systems
- Natural Language Processing (NLP)
  - Story understanding
  - Speech recognition
  - Question answering

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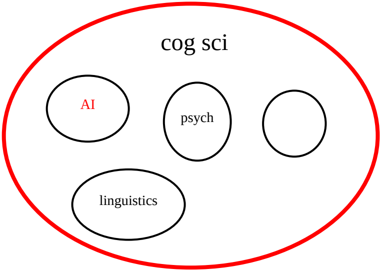
Some Subareas of AI...

- Perception
- Vision
- Robotics
- Machine Learning
- Pattern Recognition



Intelligence is (?) Reasoning + Knowledge

- Reasoning
  - Universal inference methods
  - "Weak" methods, e.g. hill climbing
  - Domain-independent search through symbolic state spaces
  - Problem-solving/planning theorem proving - first principles
- Knowledge
  - Universal methods $\rightarrow$ combinatorial explosion
  - "Strong" methods:
    - Heuristics
    - Domain-dependent knowledge
    - Shallow deductions
  - ..... Expert systems

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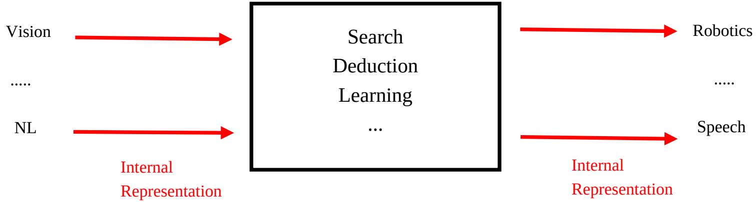
Goal of AI

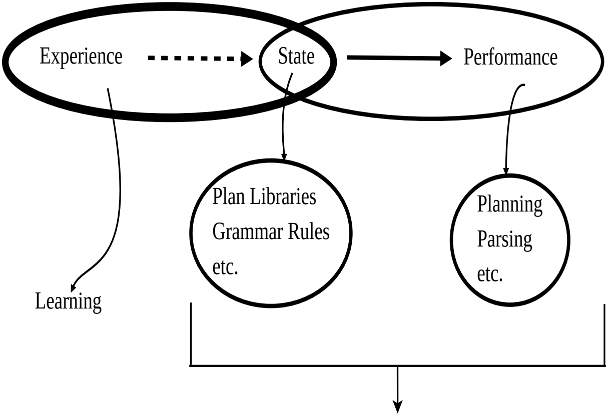
Build a person / animal



Internal representation:

- Not NL
- All representations inter-translatable
- Unambiguous, explicit referents, only gist remembered
- Support inferences

Why is AI not just "Learning"?



Characterize **what** it is that is to be learned!

- To learn anything you should already “know” a lot
- Without strong clues of domain, nothing is learned
- There are many kinds of learning...