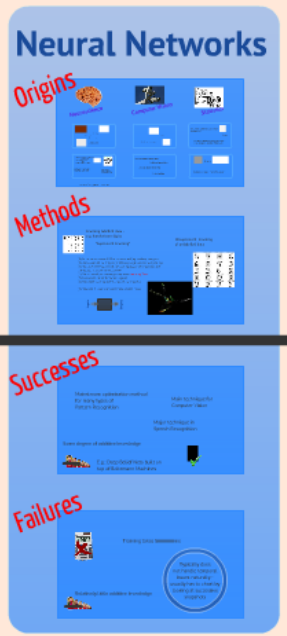
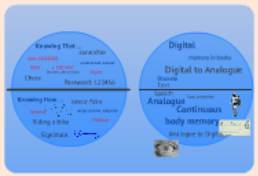
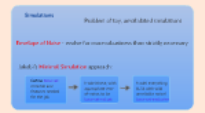
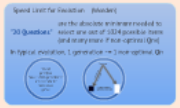
Perspectives on AI

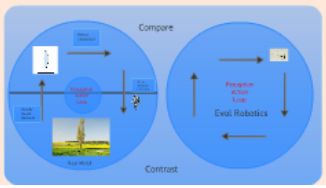
Inman Harvey











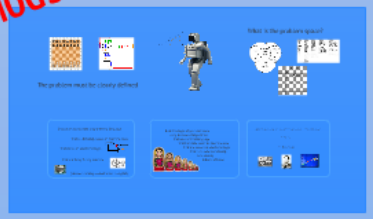
Perspectives on AI

Inman Harvey

Classical AI

Origins

Methods



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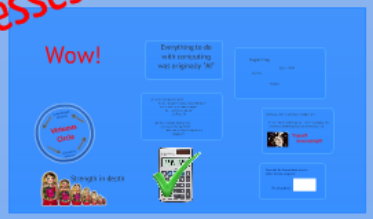
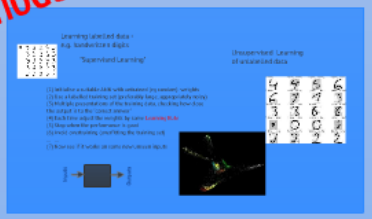


Failures

Neural Networks

Origins

Methods



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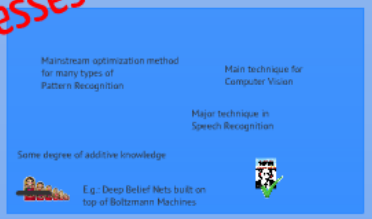
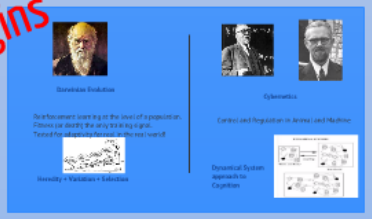


Failures

Evolutionary Robotics

Origins



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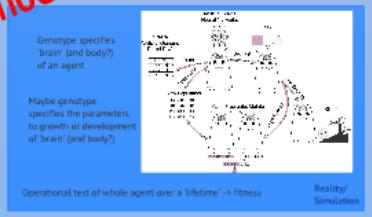

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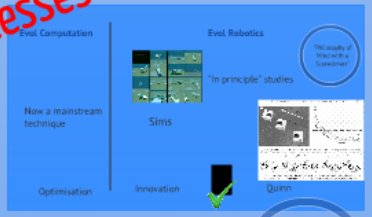

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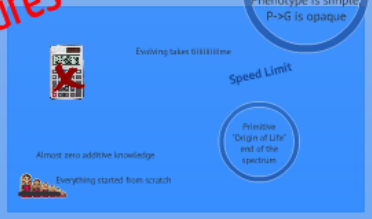

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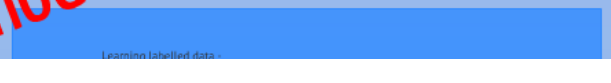


SmartData

What kind of Data?

What kind of Smart?

"Knowing How" versus "Knowing That"

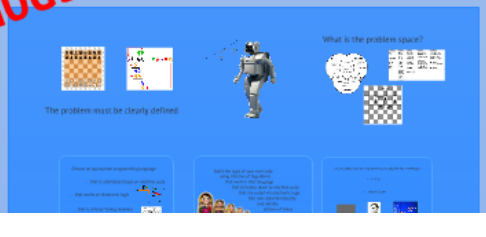
Context sensitivity

Perspectives on AI

Classical AI

Origins

Methods



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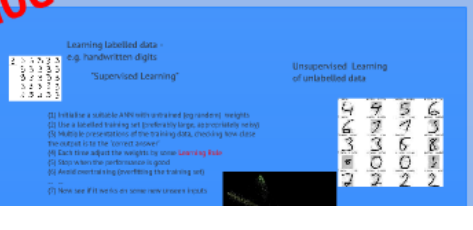

Thought

differentiates
ns from other animals"

bodied Logic
y constrained worlds
no noise

"AI always promises, never delivers"

Unfair !

Once delivered, ceases being called AI

Computer programming
Google
cell phones
... ...

Any sufficiently advanced technology is
indistinguishable from magic -- AC Clarke

$x^2 + y^2 = z^2$

Rational Thought

"What differentiates
Humans from other animals"

Disembodied Logic
Rigidly constrained worlds
Little/no noise
Chess

Adaptive Behaviour
Robust to changing context

4,000 kms each way
3 or 4 generations/cycle
Weighs a few milligrams
magnetic sense, sun compass
circadian clock, photoreceptors,
smell ... ...

"AI always prom

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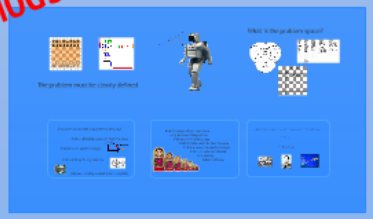

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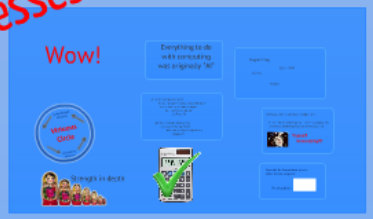

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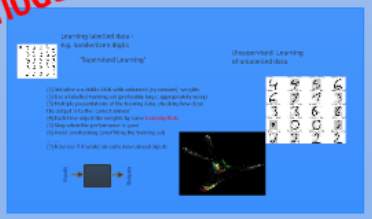

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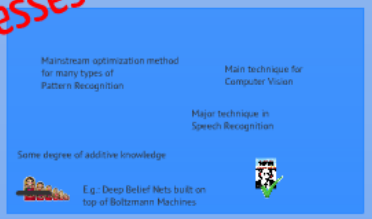

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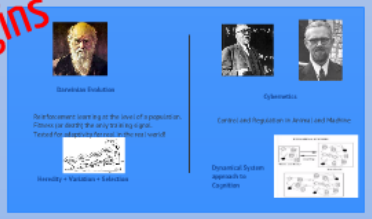

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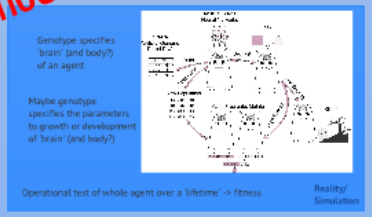

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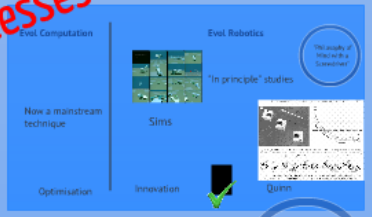

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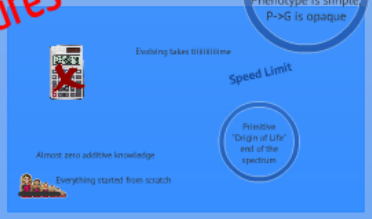

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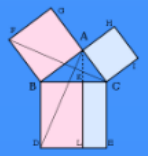



Rational, disembodied thought

Written down - Permanent Record

Accounting, calculating

Deterministic, reproducible algorithms
- same results every time.

Ideas can be separated from immediate context

Technology-driven, technology-driving

From Clay Tablets
to Printing Presses
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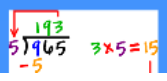
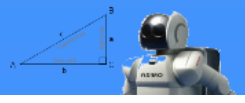
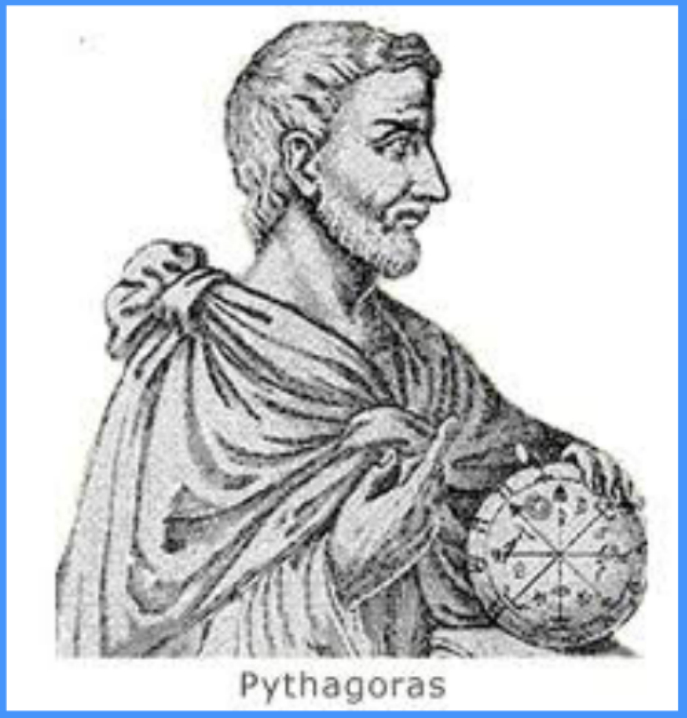
General Purpose Computing

The Human Brain is just another form of computer with a different Operating System

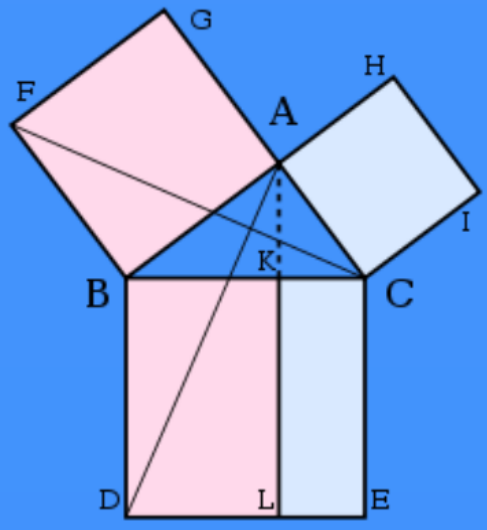
Methods

What is the problem space?

Pythagoras

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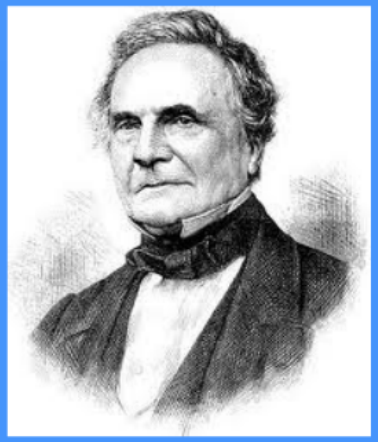

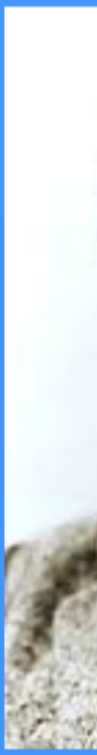

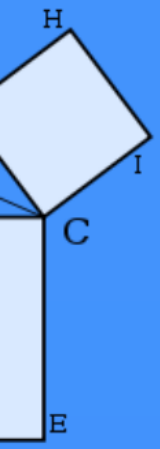
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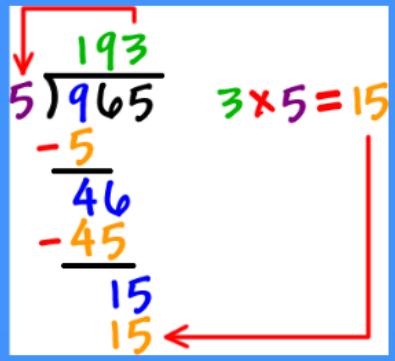
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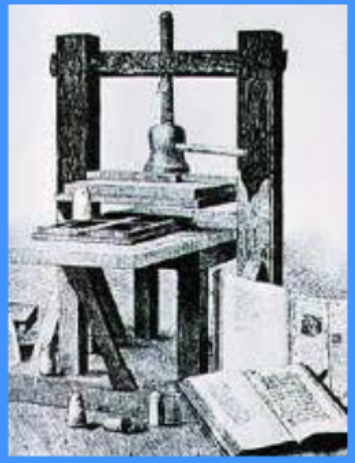
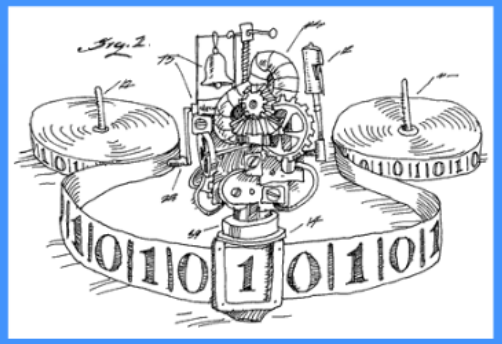
46
-45
15
15
3×5=15





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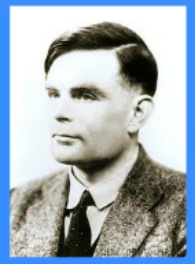

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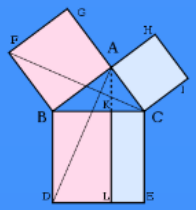

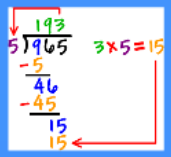

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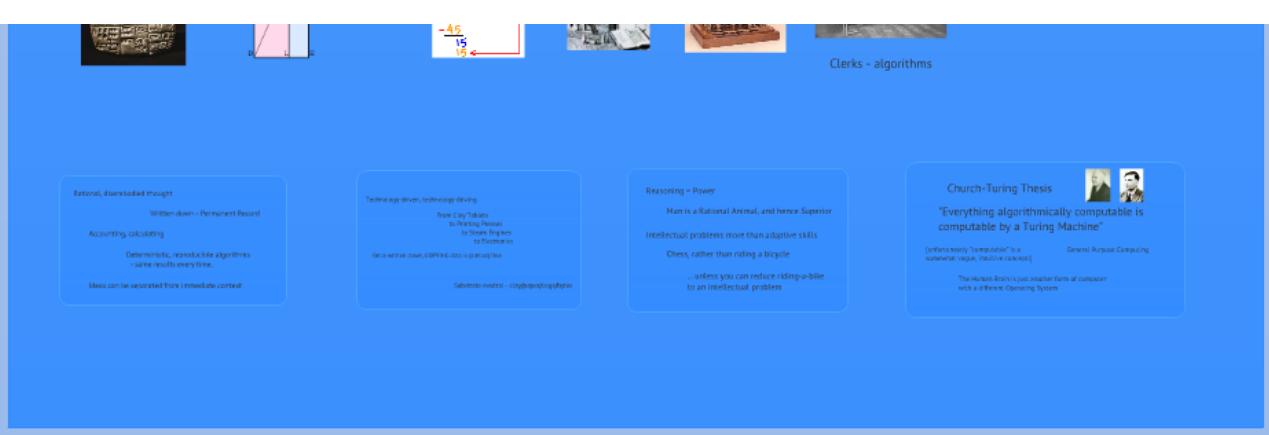

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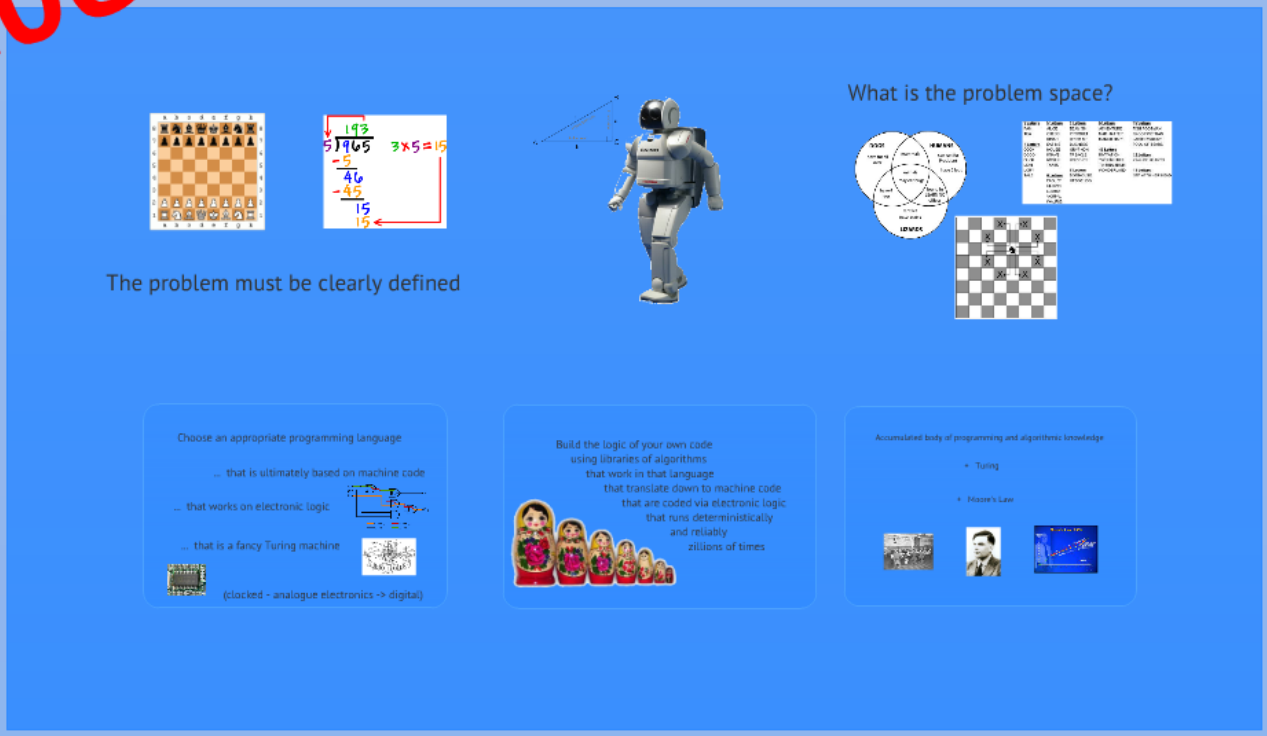
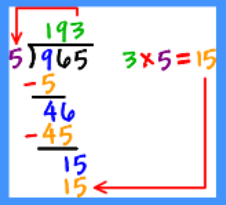
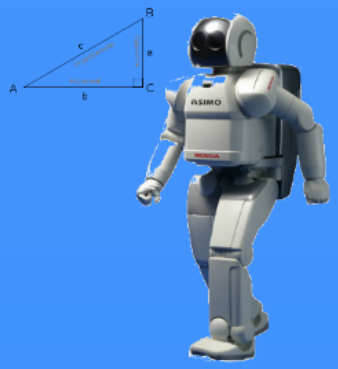


sses

ods



The problem must be clearly defined



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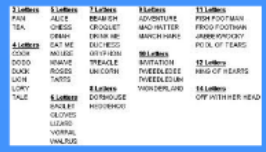
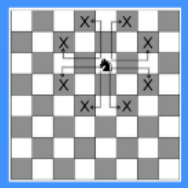
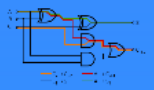




Choose an appropriate programming language

... that is ultimately based on machine code

... that works on electronic logic



... that is a fancy Turing machine

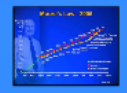
(clocked - analogue electronics -> digital)

Build the logic of your own code
using libraries of algorithms
that work in that language
that translate down to machine code
that are coded via electronic logic
that runs deterministically
and reliably
zillions of times

Accumulated body of programming and algorithmic knowledge

+ Turing

+ Moore's Law



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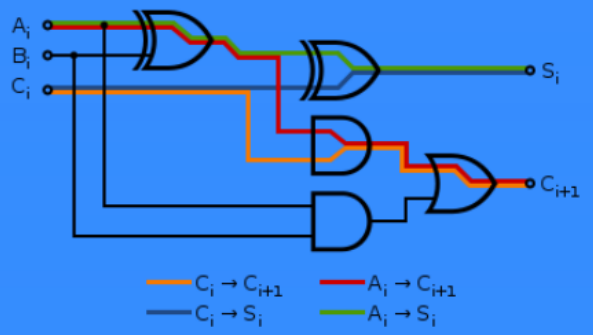

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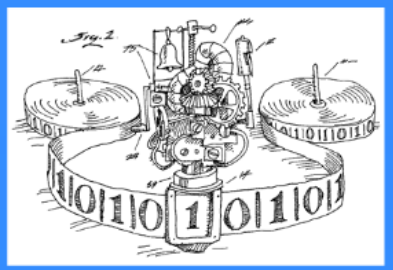

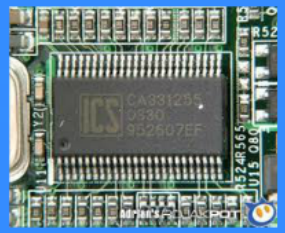

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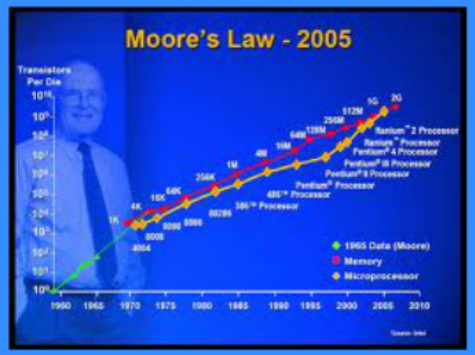

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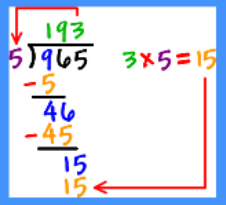
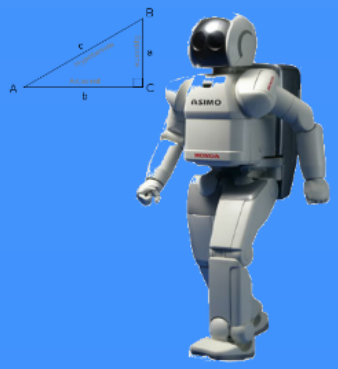
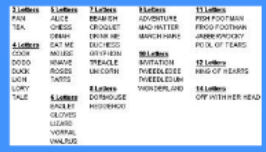
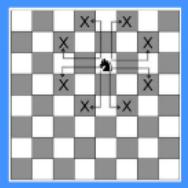


The problem must be clearly defined



What is the problem space?

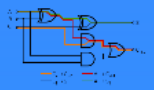




Choose an appropriate programming language

... that is ultimately based on machine code

... that works on electronic logic



... that is a fancy Turing machine

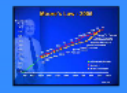
(clocked - analogue electronics -> digital)

Build the logic of your own code
using libraries of algorithms
that work in that language
that translate down to machine code
that are coded via electronic logic
that runs deterministically
and reliably
zillions of times

Accumulated body of programming and algorithmic knowledge

+ Turing

+ Moore's Law



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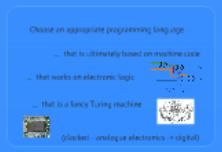
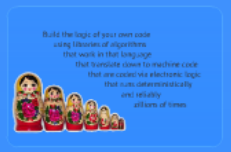
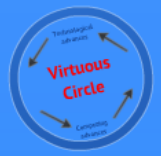


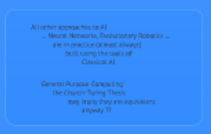


Successes

Wow!

Everything to do with computing was originally "AI"





Strength in depth

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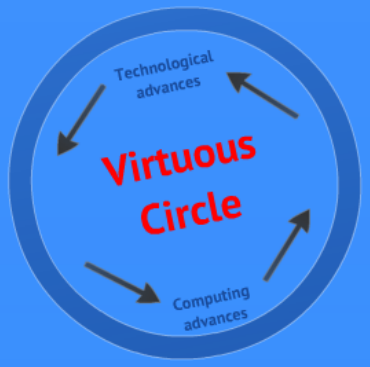
Programming

Digital Media

Internet

Phones

... ...



All other approaches to AI
... Neural Networks, Evolutionary Robotics ...
are in practice (almost always)
built using the tools of
Classical AI

'General Purpose Computing'
the Church-Turing Thesis
may imply they are equivalent
anyway ??

Computationalist approach to Cognition

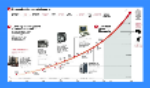
If this kind of reasoning is all there is to cognition, then we can download our brains onto a chip!

Yippee!!
Immortality!!!

Strength in depth

Or maybe the human brain is just a rather inferior computer?

The Singularity?



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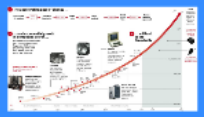

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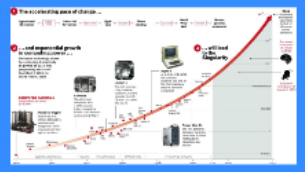

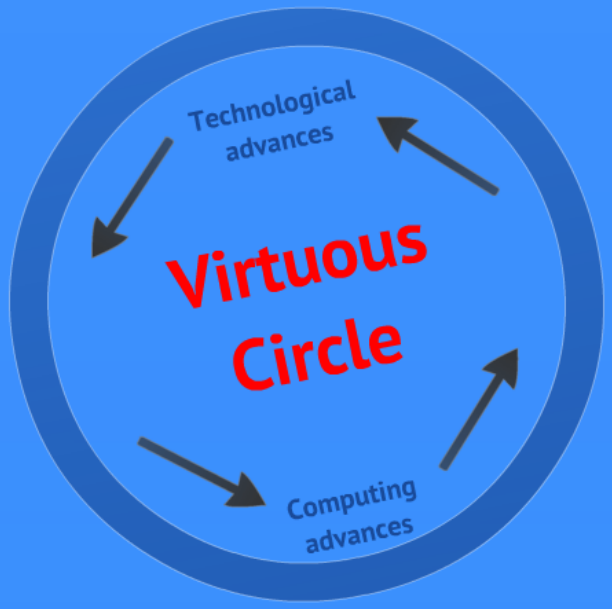

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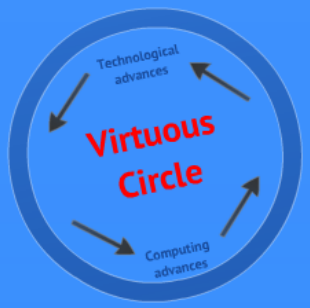

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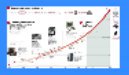

Failures

The Frame Problem

What is the context?

How much is relevant?

What can I ignore?

Shakey the Robot

Dynamics ← series of Static snapshots

Brook's criticisms
Behavior-based robotics
Subsumption architecture

es

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Ignored or Forgot Evolution

3,800 million years of evolved adaptive behaviour

Only ~0.1 million years of language and reasoning

Logic and reasoning is a specialised niche form of adaptive behaviour

NOT

adaptive behaviour is a specialised application of logical reasoning

Confusing the Map with the Territory

Working with maps
is working with Descriptions
- 'Knowing That'

GOFAI !

The Frame Problem

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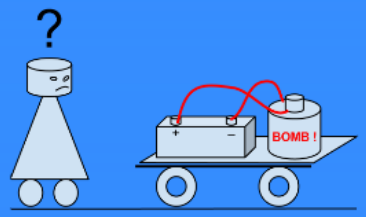

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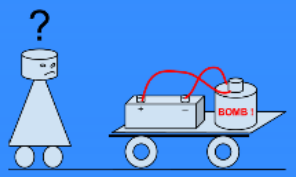

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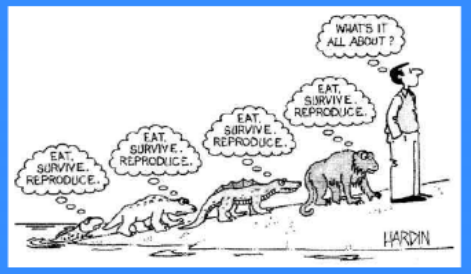

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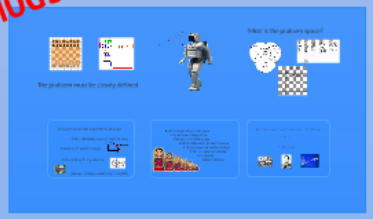
Perspectives on AI

Inman Harvey

Classical AI

Origins

Methods



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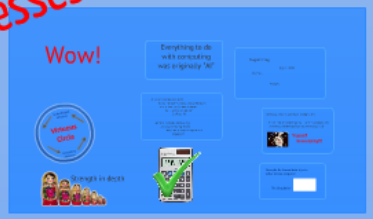
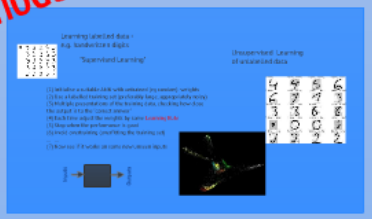


Failures

Neural Networks

Origins

Methods



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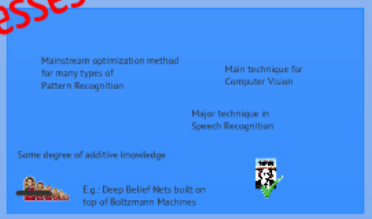
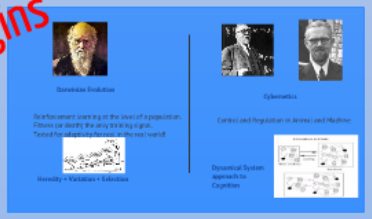


Failures

Evolutionary Robotics

Origins



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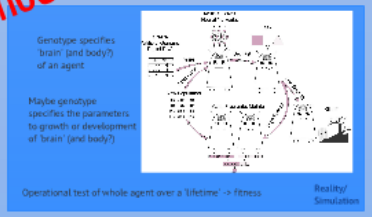

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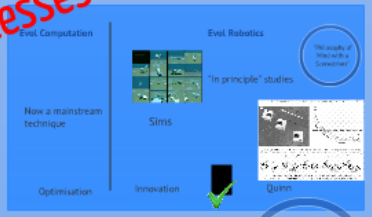

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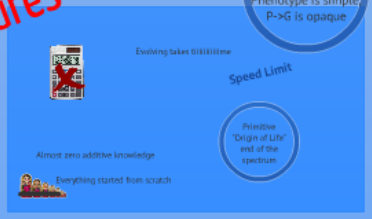

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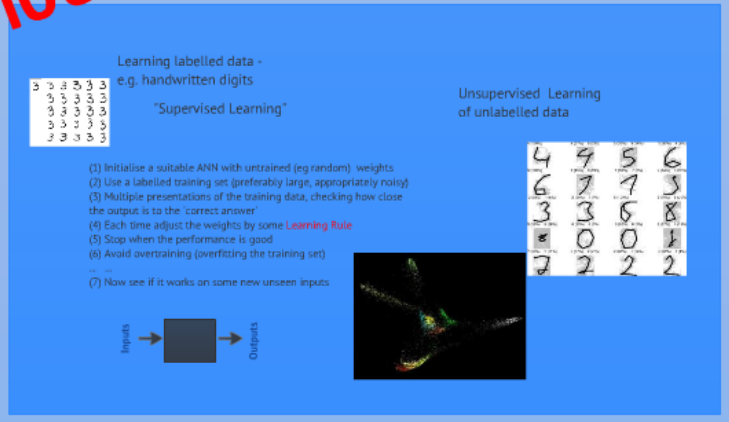

Evolutionary

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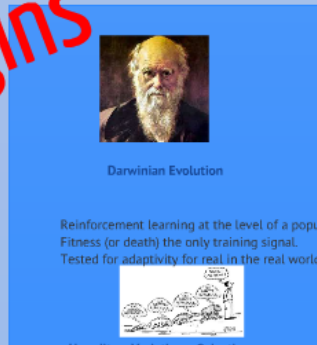

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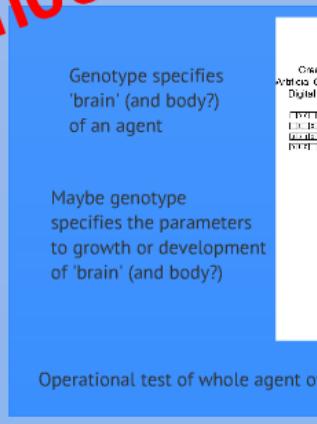

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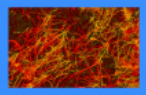
Neuroscience

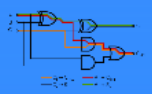
Computer Vision

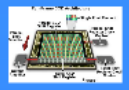
Statistics

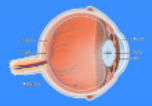


The brain has lots of simple (?) components networked together.
Inputs ->
Lots of neural 'processing'
-> Outputs

McCulloch & Pitts







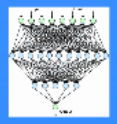
Pattern Recognition
Noisy 2D input array -> Reliable classification

Recognising patterns in data is what statisticians do

Bayes

Sometimes Artificial Neural Nets are just 'doing statistics a slightly different way'

Neurons = 'transistors' or 'logic nodes'
'activation level'
axons/dendrites = 'wires'
'signal'
synaptic strengths = 'weights'



Updating rule - e.g. Hebb rule
for updating weights/synapses

'Simple neurons'
'Simple architecture'
'Complexity from SIZE'

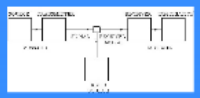
Classical Reasoning has problems with this

Parallel processing of noisy data

A lot of what human brains do is vision

Practical applications

Shannon

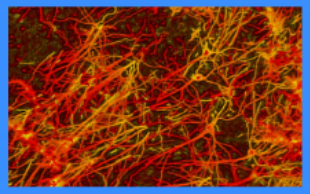


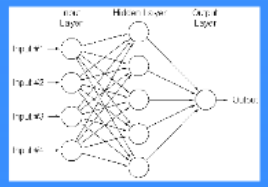
Pattern Recognition ~ 'Signal from Noise'

Time, synfire, gases - mention

ds

Neuroscience





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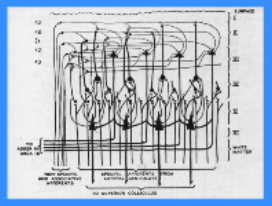

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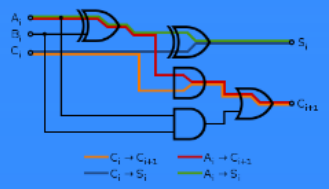

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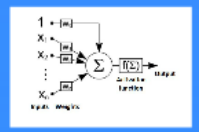

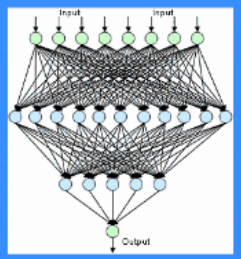

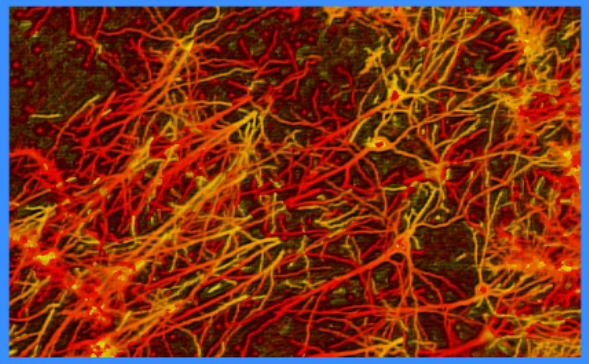

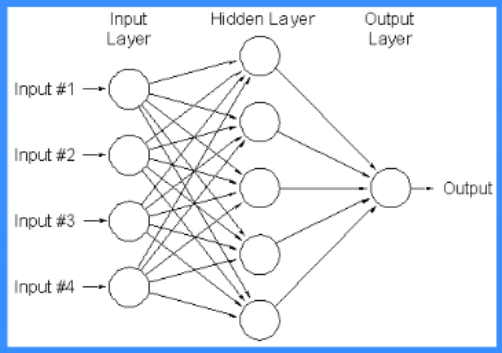

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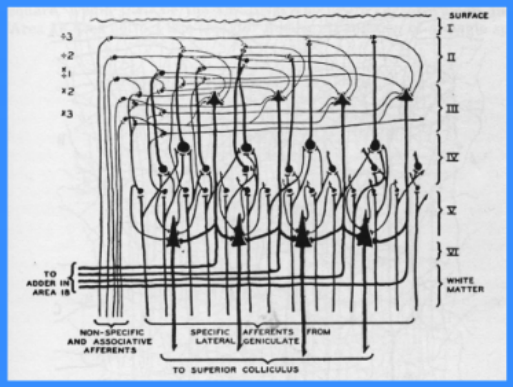
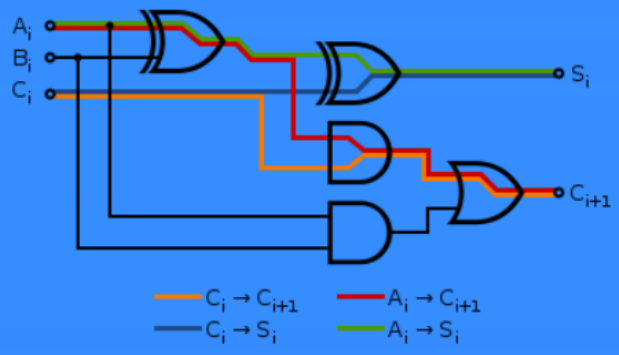
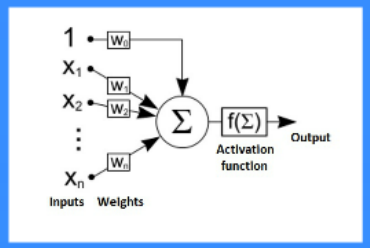
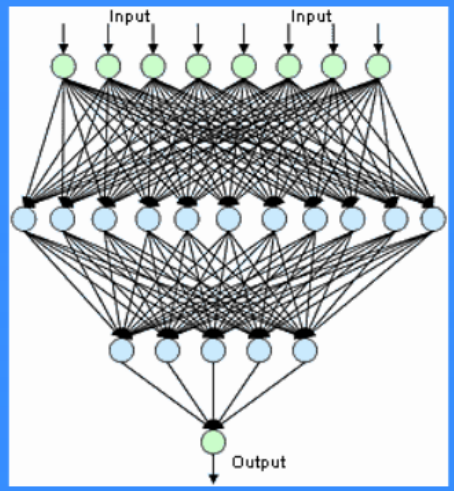


McCulloch & Pitts



Neurons = 'transistors' or 'logic nodes'
'activation level'
axons/dendrites = 'wires'
'signal'
synaptic strengths = 'weights'





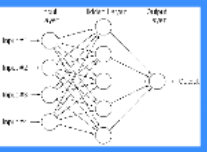
Updating rule - e.g. Hebb rule
for updating weights/synapses

'Simple neurons'
'Simple architecture'
'Complexity from SIZE'

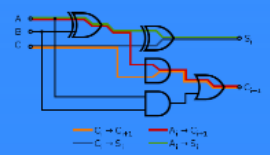
ce

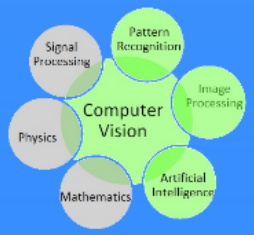
Computer Vision

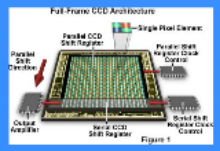
s

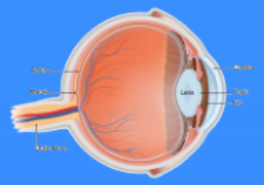


mponents



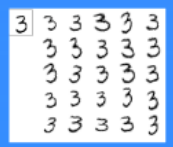






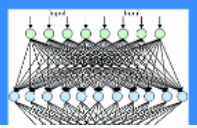
CCD = Retina

Pattern Recognition
Noisy 2D input array -> Reliable classification

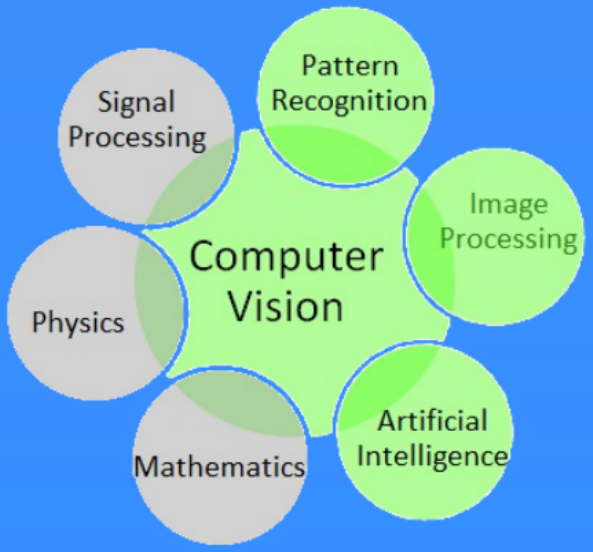


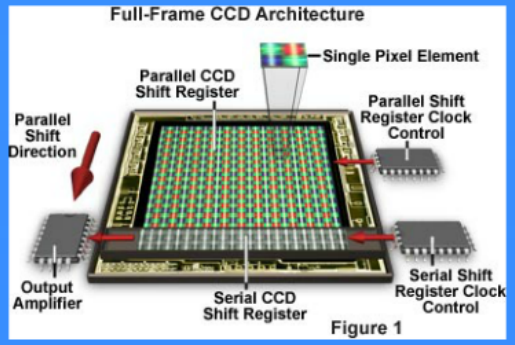
Recognising patt
statisticians do

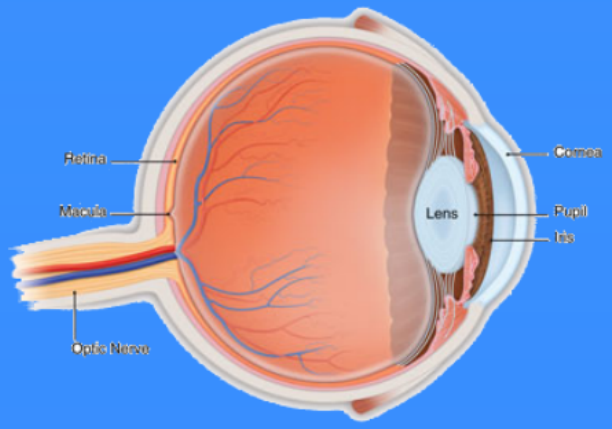
Sometimes A
'doing statist



Classical Reasoning has problems with this







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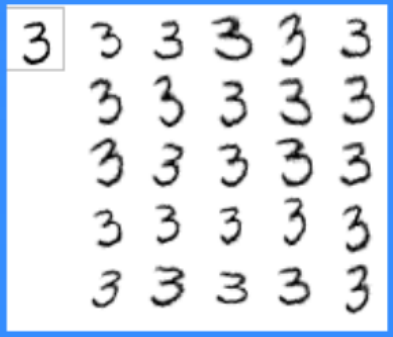


Classical Reasoning has problems with this

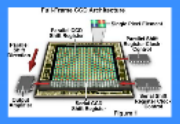
Parallel processing of noisy data

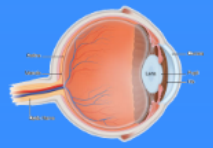
A lot of what human brains do is vision

Practical applications

ter Vision

Statistics





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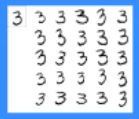

>> Reliable classification

problems with this

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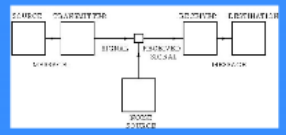
Practical applications

Recognising patterns in data is what statisticians do

Bayes

Sometimes Artificial Neural Nets are just 'doing statistics a slightly different way'

Shannon



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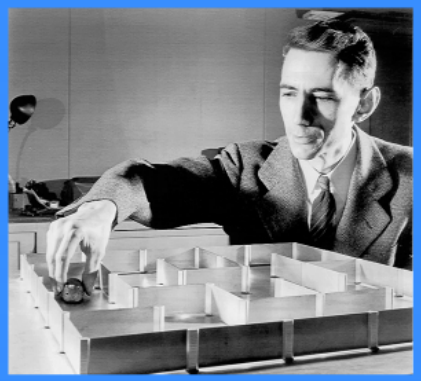

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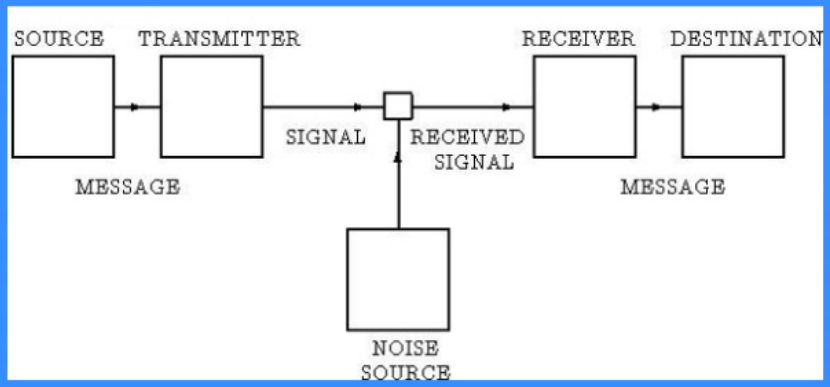


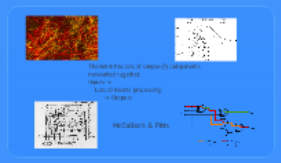
Pattern Recognition ~ 'Signal from Noise'

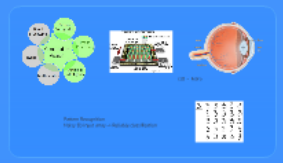
Origins

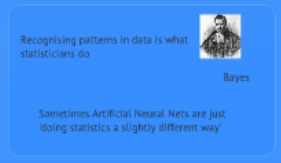
Neuroscience

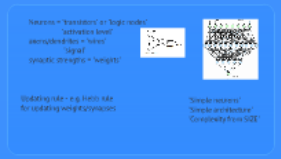
Computer Vision

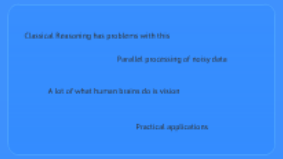
Statistics





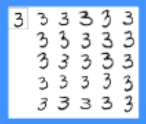






Time, synfire, gases - mention

Methods

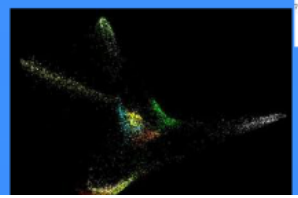


Learning labelled data -
e.g. handwritten digits

"Supervised Learning"

Unsupervised Learning
of unlabelled data

(1) Initialise a suitable ANN with untrained (eg random) weights
(2) Use a labelled training set (preferably large, appropriately noisy)
(3) Multiple presentations of the training data, checking how close the output is to the 'correct answer'
(4) Each time adjust the weights by some Learning Rule
(5) Stop when the performance is good
(6) Avoid overtraining (overfitting the training set)
... ...
(7) Now see if it works on some new unseen inputs



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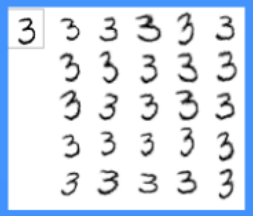

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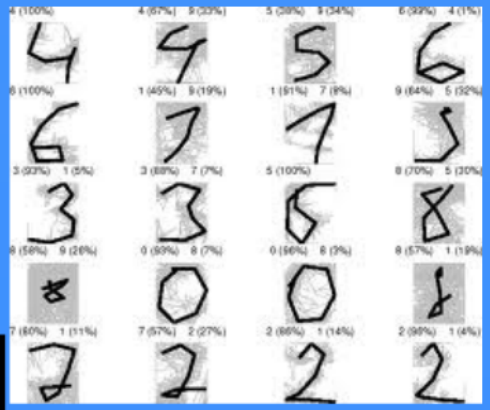

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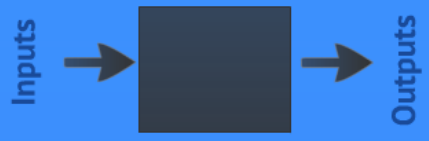

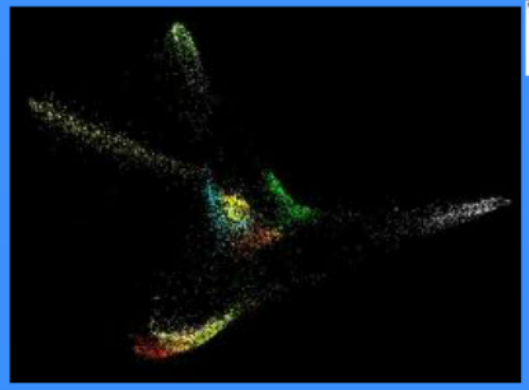

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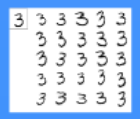

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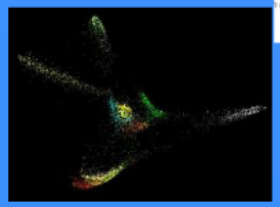

Successes

Mainstream optimization method
for many types of
Pattern Recognition

Main technique for
Computer Vision

Major technique in
Speech Recognition

Some degree of additive knowledge

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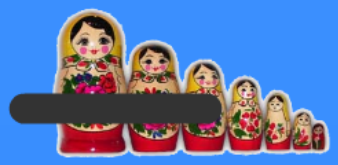

E.g.: Deep Belief Nets built on
top of Boltzmann Machines

Majo
Spee

Some degree of additive knowledge

E.g.: Deep Belief Nets built on top of Boltzmann Machines

Succe

Mainstream optimization method
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Some degree of additive knowledge

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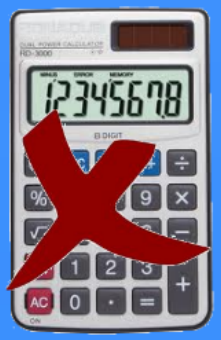
Failures

Training takes tiiiiiiiiiiiime

Typically does
not handle temporal
issues naturally -
usually has to cheat by
looking at successive

Relatively little additive knowledge

res



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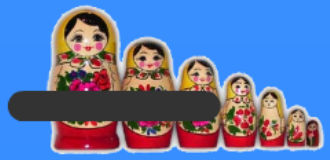

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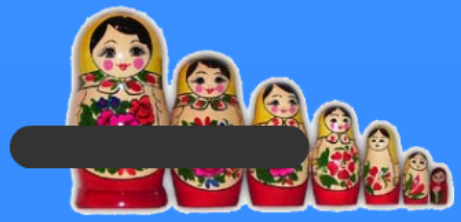

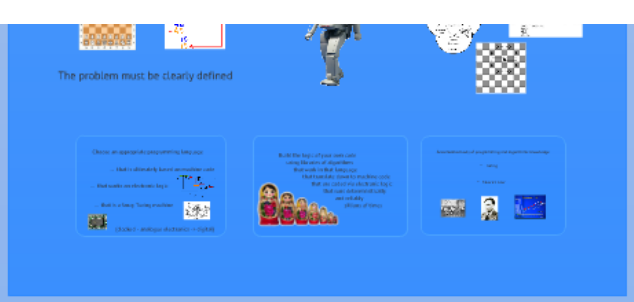

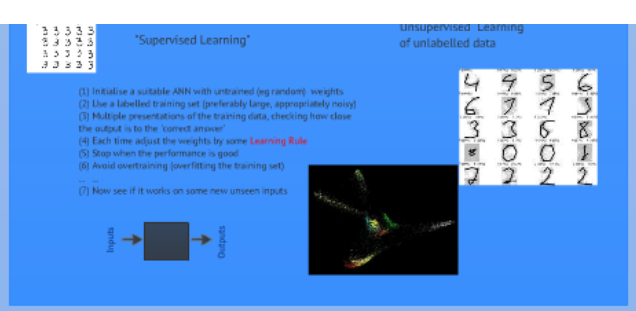

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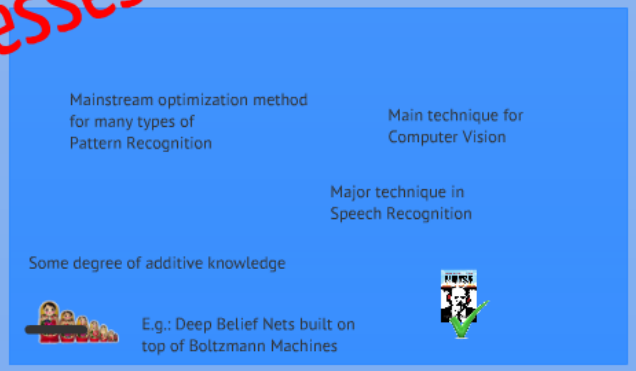
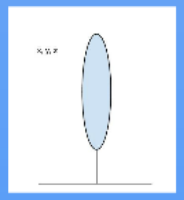


Failures

Failures

Compare

Reason
Classical AI



Perception
Action
Loop

Action
(someone
else's job)

Classify
Neural
Networks

Real World

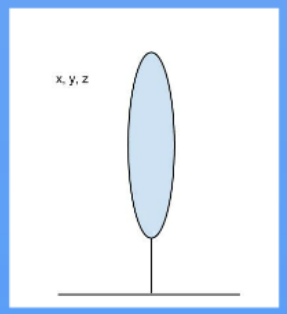
Perception
Action
Loop

Evol Robotics

Contrast

Compare

Reason
Classical AI



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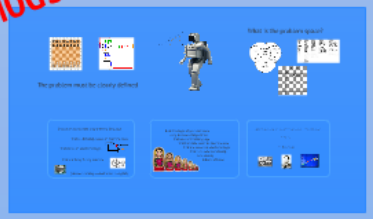
Perspectives on AI

Inman Harvey

Classical AI

Origins

Methods



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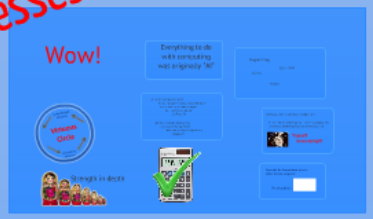

Failures

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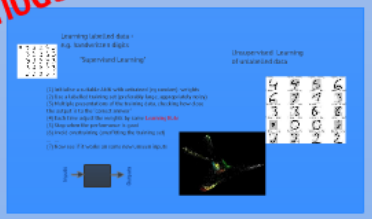

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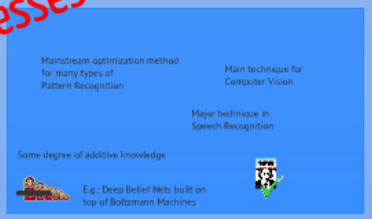
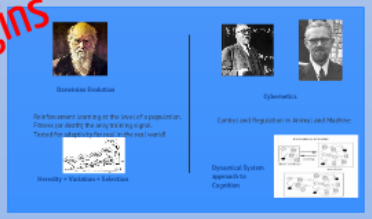


Failures

Evolutionary Robotics

Origins



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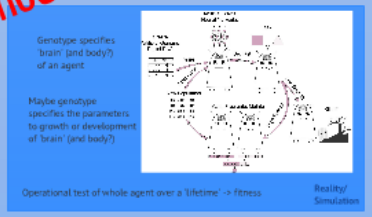

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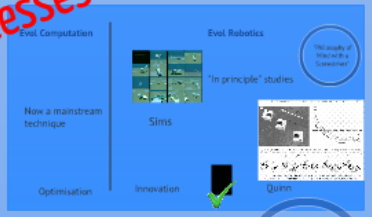

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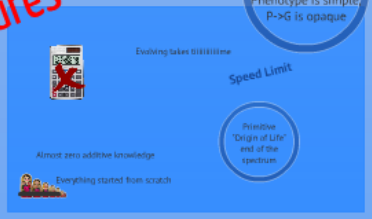

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Evolutionary Robotics

Origins

Darwinian Evolution

Reinforcement learning at the level of a population.
Fitness (or death) the only training signal.
Tested for adaptivity for real in the real world!

Heredity + Variation + Selection

Cybernetics

Control and Regulation in Animal and Machine

Dynamical System approach to Cognition

Methods

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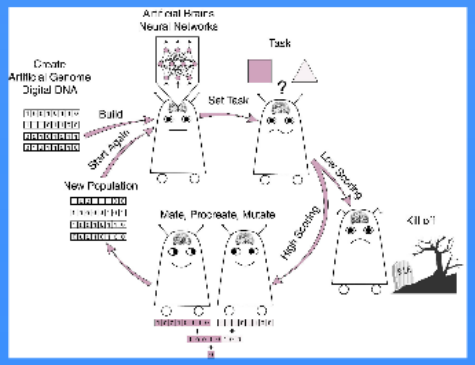

Operational test of whole agent over a 'lifetime' -> fitness

Reality/ Simulation

ns

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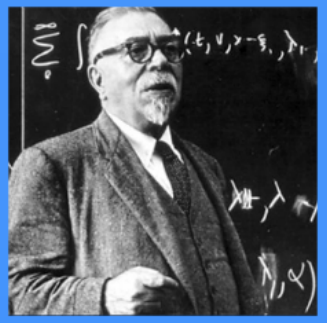

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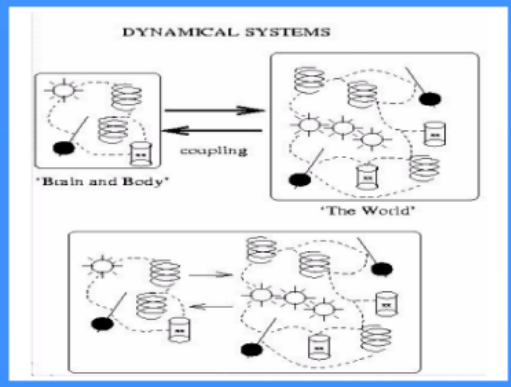

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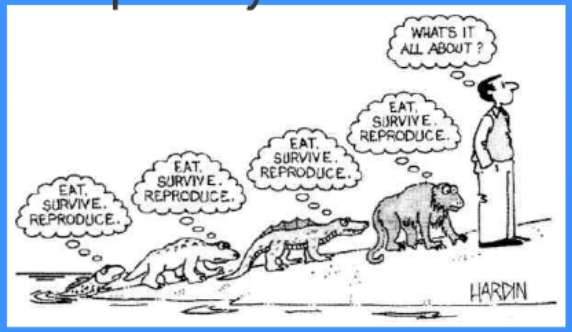

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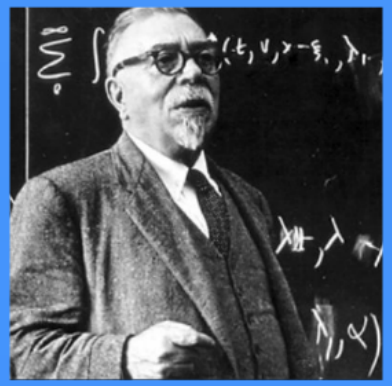

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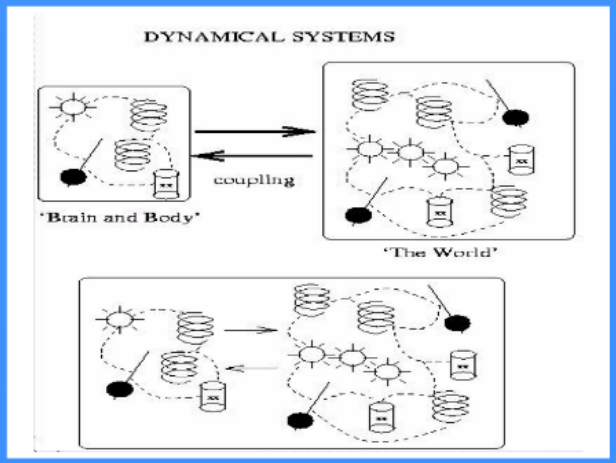

Evolutionary Robotics

Origins

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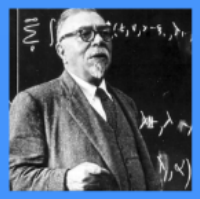

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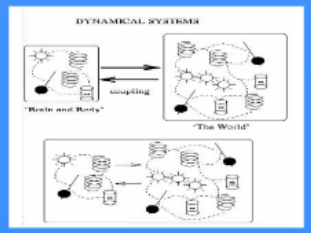

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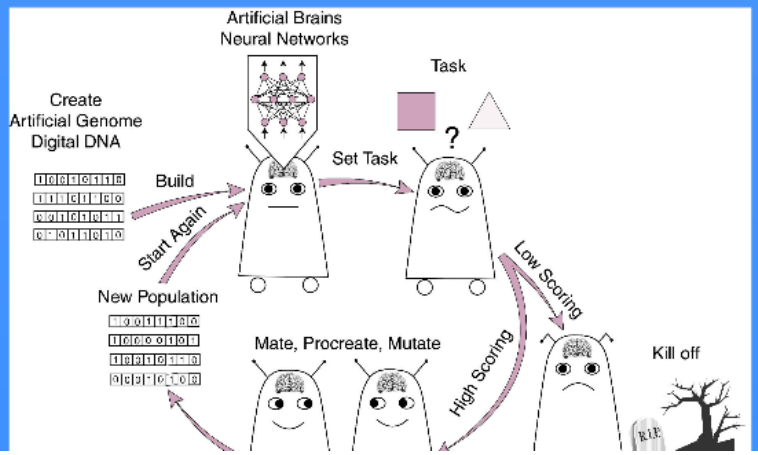

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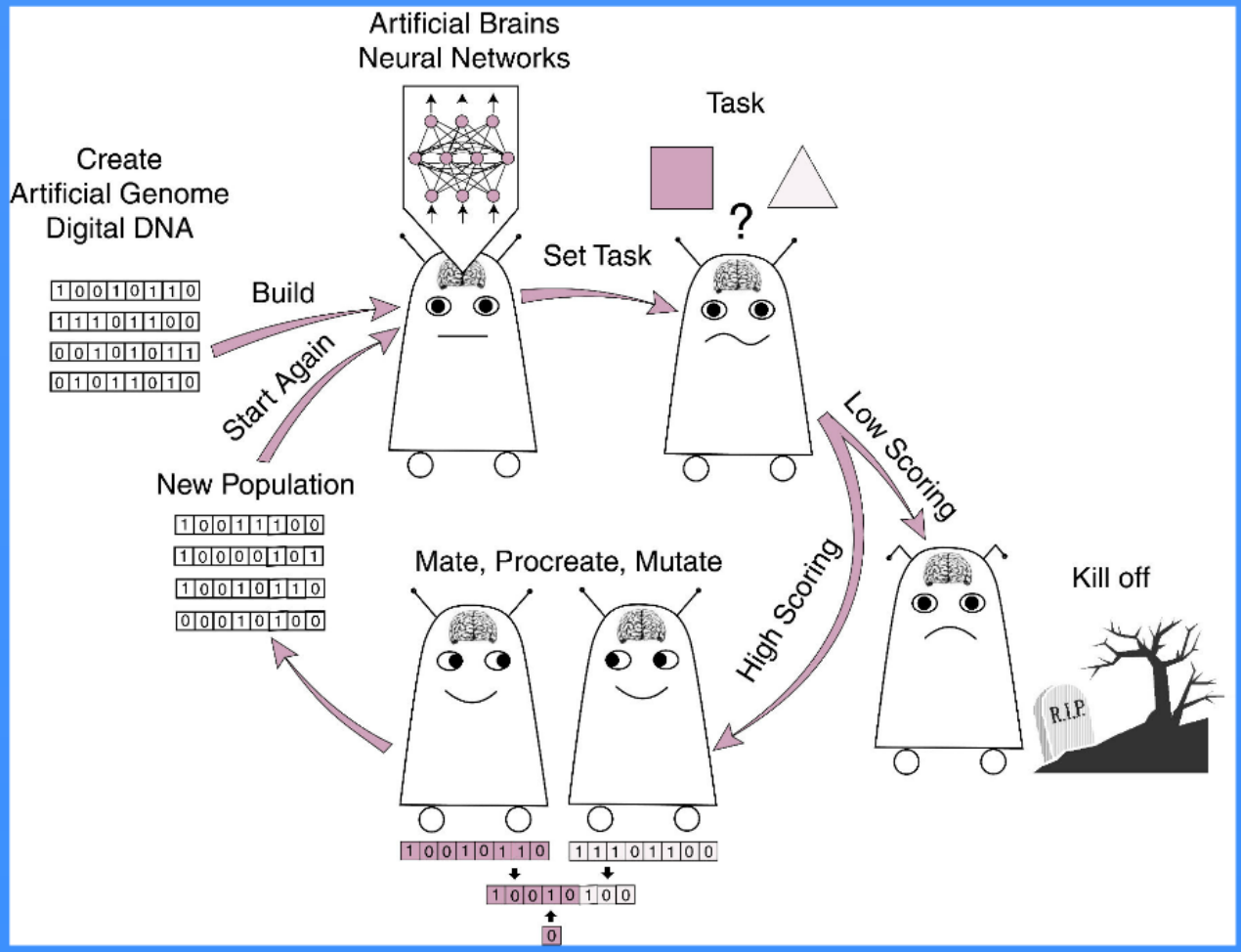
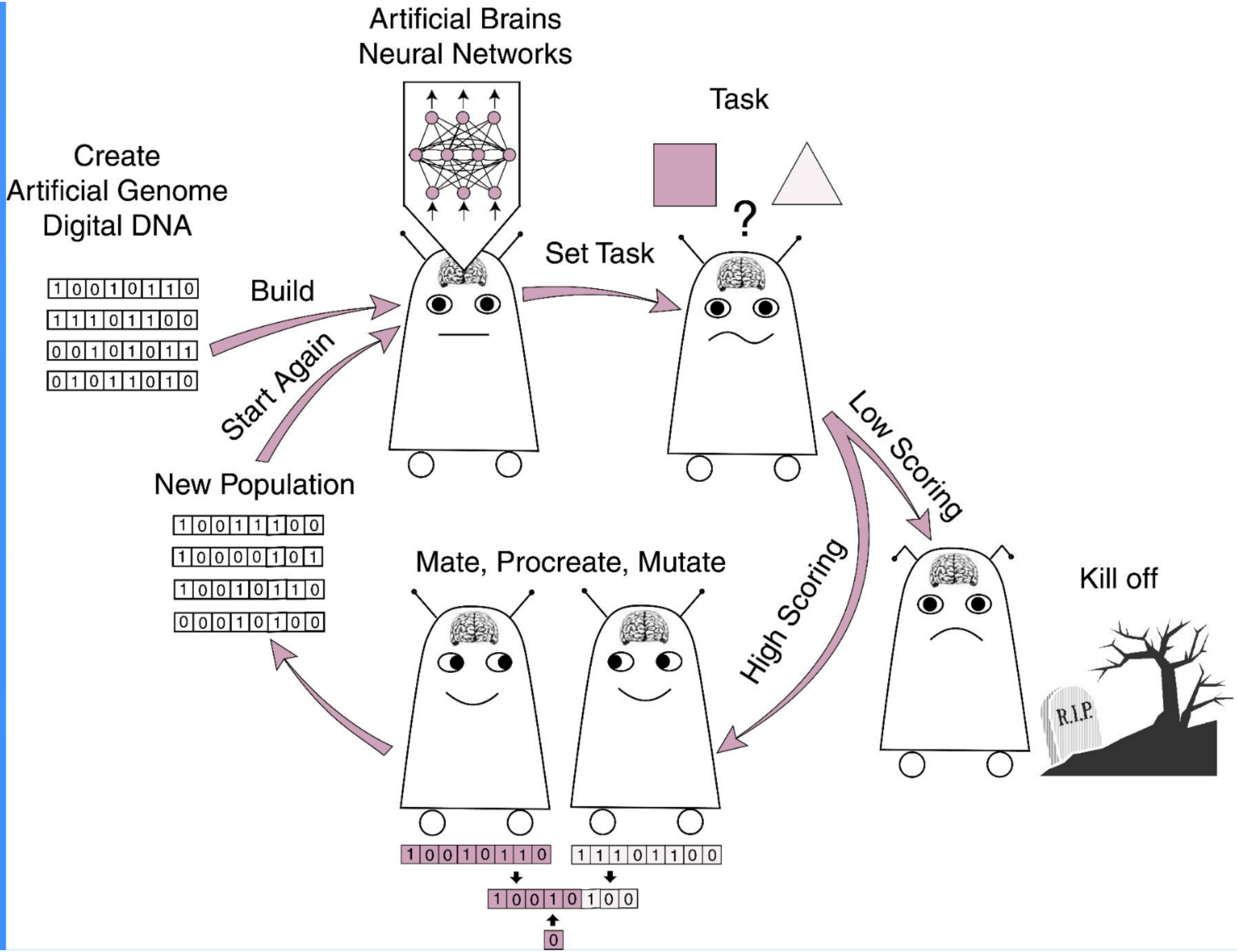


Operational test of whole agent over a 'lifetime' -> fitness

Reality/ Simulation


Artificial Brains
Neural Networks
Task
Create
Artificial Genome
Digital DNA
Build
Start Again
Set Task
?
Low Scoring
New Population
Mate, Procreate, Mutate
High Scoring
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R.I.P.

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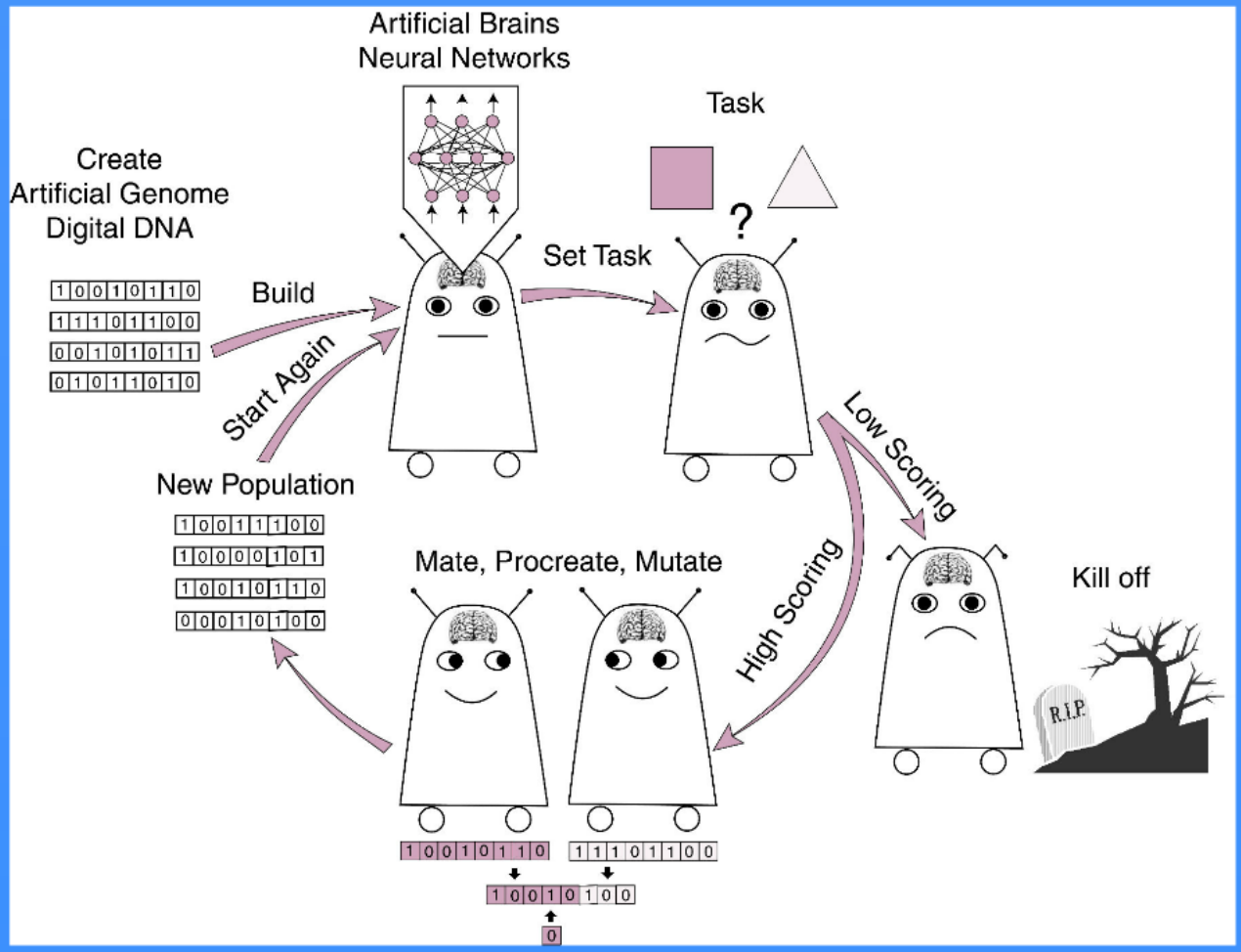

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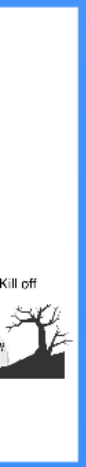

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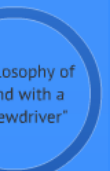
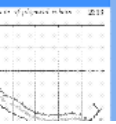


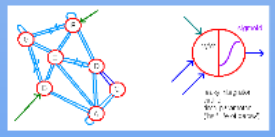


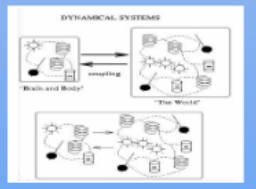
The Neural Networks evolved are typically rather than (timeless) information-filters

Real Time Dynamical Syst

E.g. CTRNNs

$$\tau_i \frac{dy_i}{dt} = -y_i + \sum_{j=1}^{n} w_{ji}\sigma(y_j - \theta_j) + I_i(t)$$





Simulations

Problem of toy, unvalidated simulat

Envelope of Noise - evolve for more robustness than strictly nec

Jakobi's Minimal Simulation approach:

Define Base set: minimal env features needed for the job → Model these, with appropriate env-of-noise, to be base-set-robust → Model everything ELSE with wild unreliable noise! base-set-exclusive

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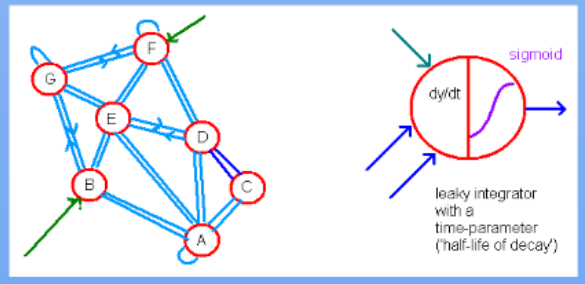

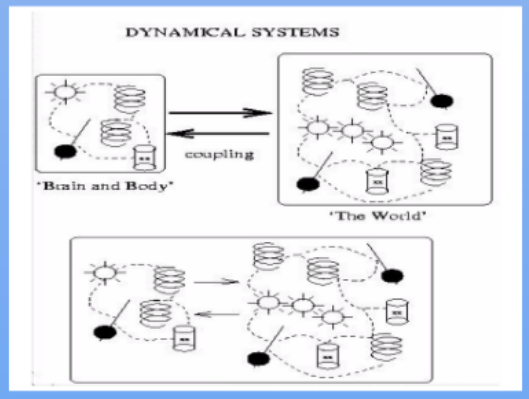

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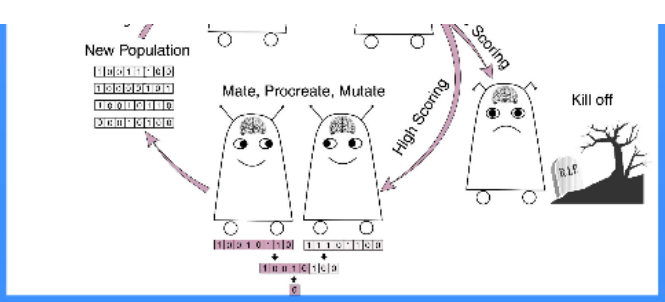

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Reality/ Simulation

Successes

Evol Computation

Now a mainstream technique

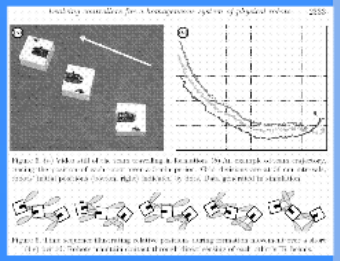
Optimisation

Evol Robotics

Sims

"In principle" studies

"Philosophy of Mind with a Screwdriver"



Quinn

Innovation

Failures

Opacity

Genotype -> Phenotype is simple, P->G is opaque

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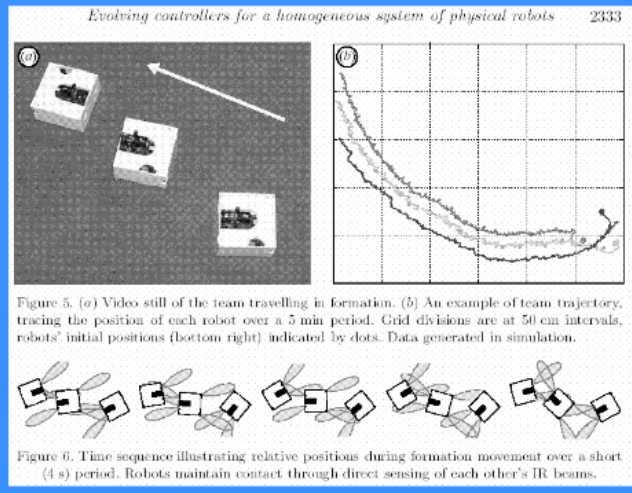

Figure 5. (*a*) Video still of the team travelling in formation. (*b*) An example of team trajectory, tracing the position of each robot over a 5 min period. Grid divisions are at 50 cm intervals, robots' initial positions (bottom right) indicated by dots. Data generated in simulation.

Figure 6. Time sequence illustrating relative positions during formation movement over a short (4 s) period. Robots maintain contact through direct sensing of each other's IR beams.

Optimisation

Innovation

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Opacity

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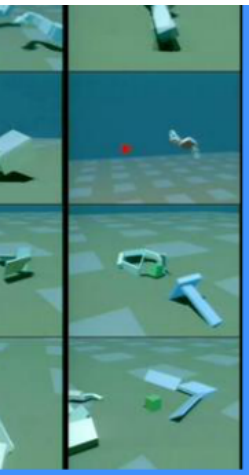
Evol Robo

Sims

"In princip



Screwdriver"

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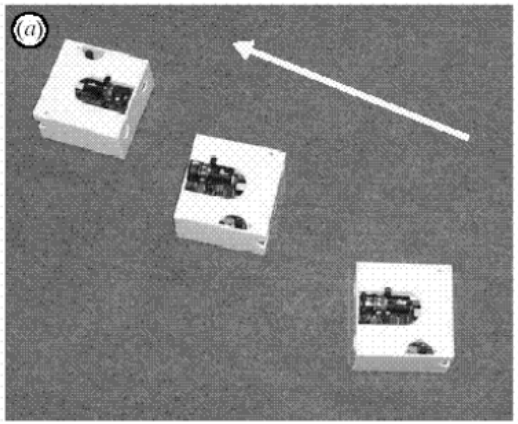

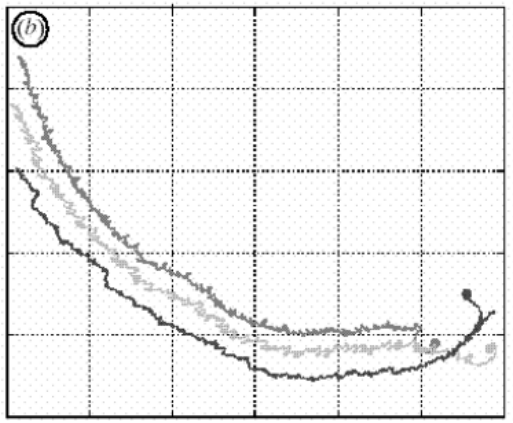

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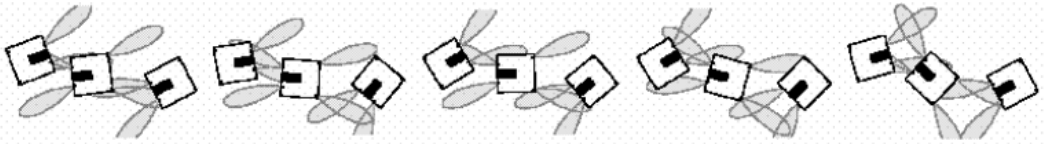

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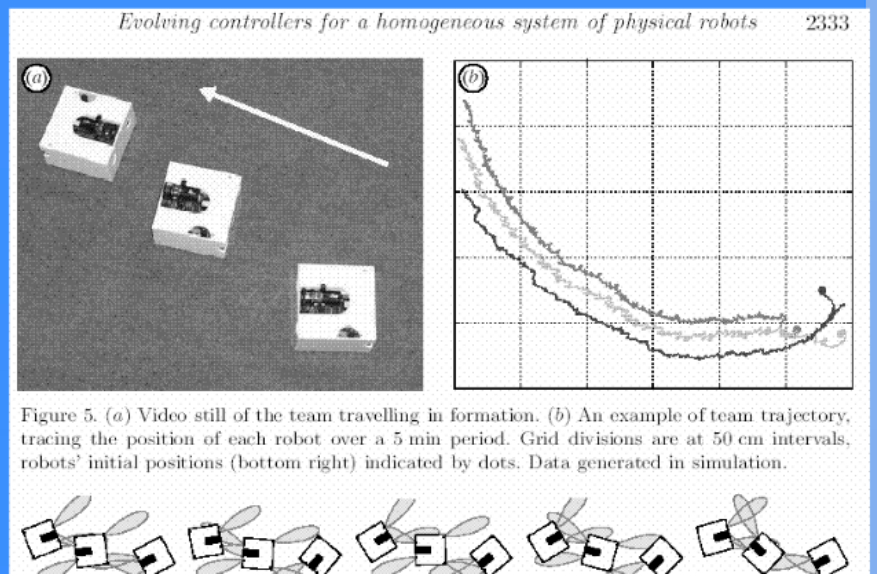

Evolving controllers for a homogeneous system of physical robots 2333

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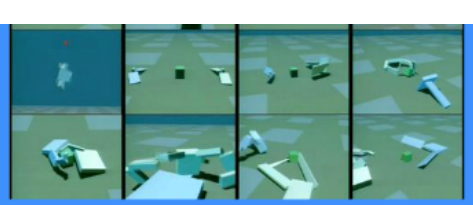
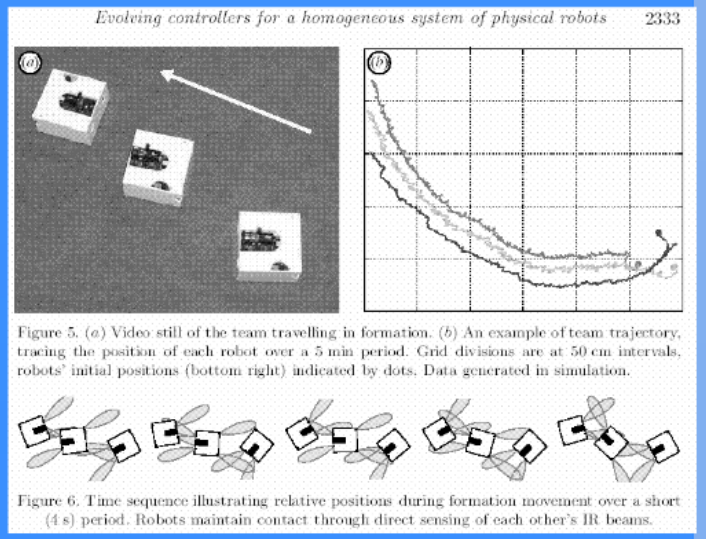


Sims



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Quinn

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Innovation

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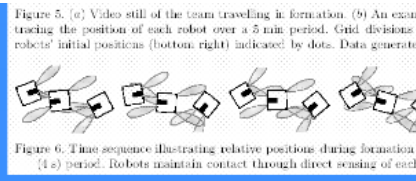
Opacity

Genotype ->
Phenotype is simple,
P->G is opaque

Optimisation

Innovation



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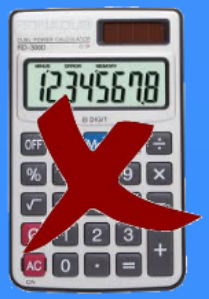

Evolving takes tiiiiiiiiiiime

Speed Limit

Primitive
"Origin of Life"
end of the
spectrum

Almost zero additive knowledge

Everything started from scratch

res

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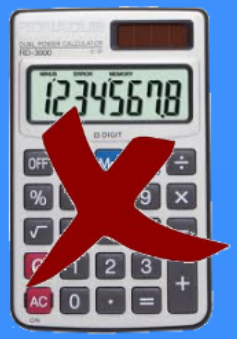

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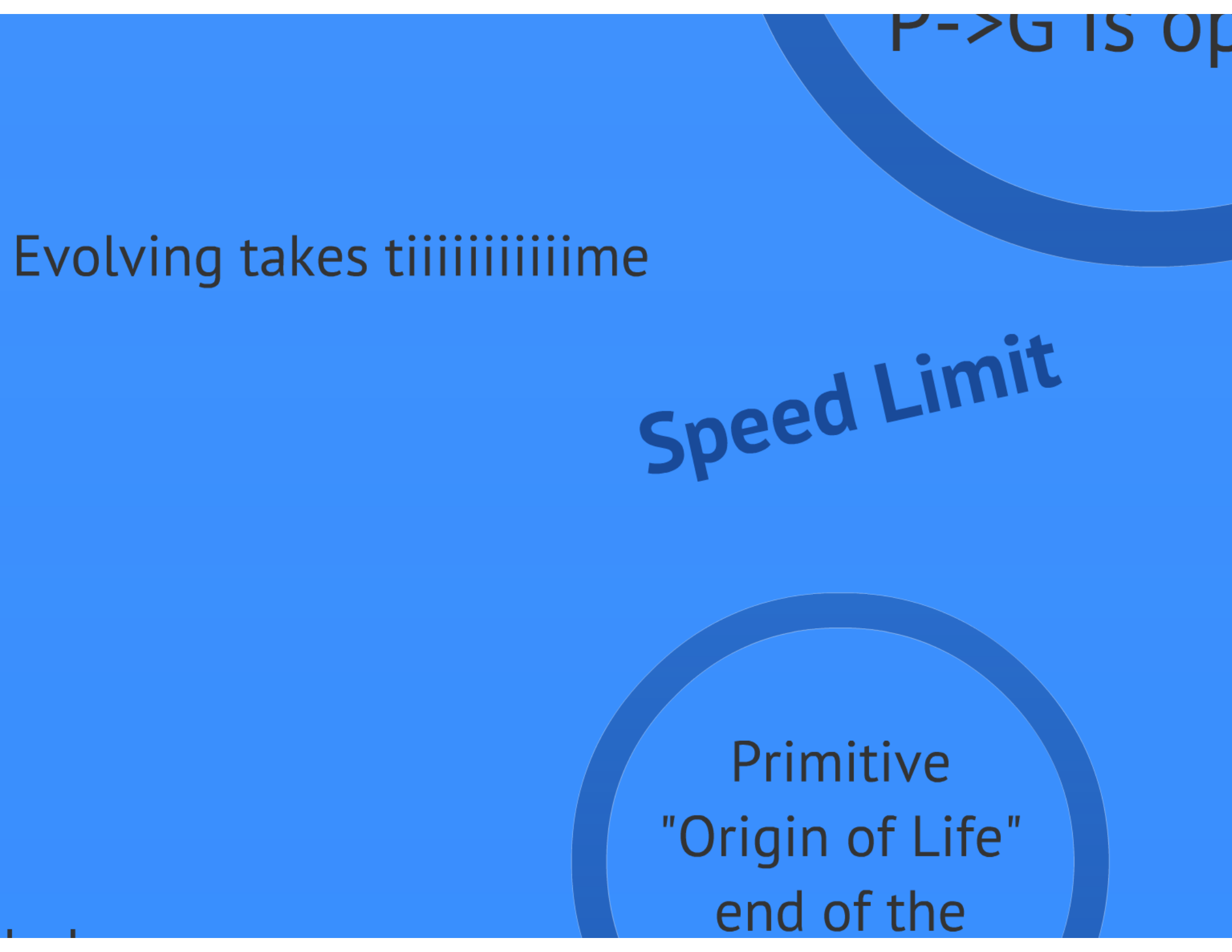
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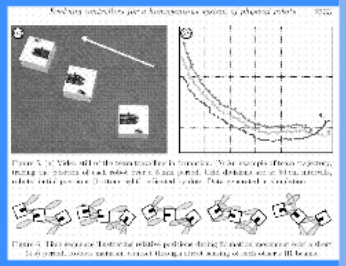

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Speed Limit for Evolution

"20 Questions"

are the ab
select on
(and man

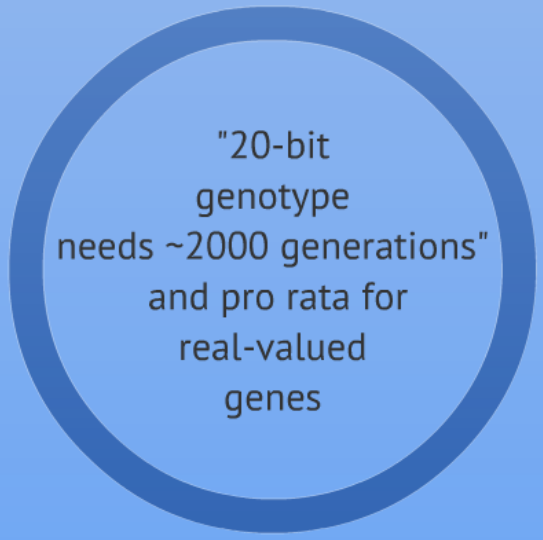
In typical evolution, 1 gen

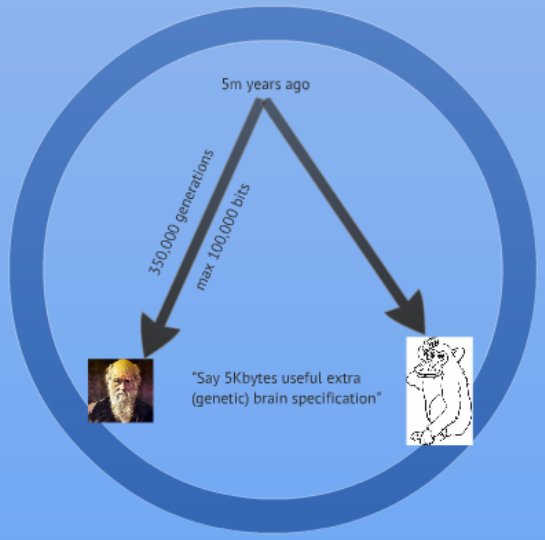
"20-bit genotype needs ~2000 generations" and pro rata for real-valued genes

Speed Limit for Evolution (Worden)

"20 Questions" are the absolute minimum needed to select one out of 1024 possible items (and many more if non-optimal Qns)

In typical evolution, 1 generation ~= 1 non-optimal Qn





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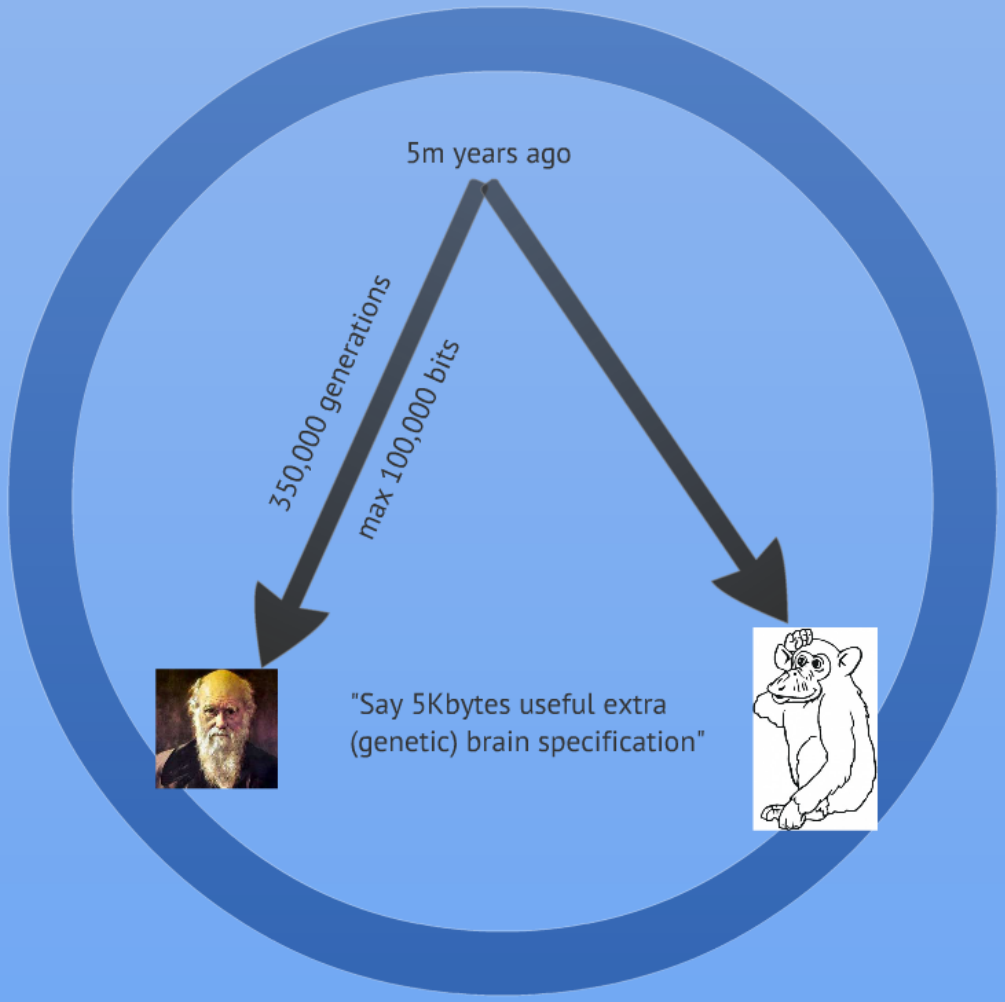

Operational test of whole agent over a 'lifetime' -> fitness

Reality/ Simulation

ses

Mainstream optimization method for many types of Pattern Recognition

Main technique for Computer Vision

Major technique in Speech Recognition

ne degree of additive knowledge

E.g.: Deep Belief Nets built on top of Boltzmann Machines

es

Training takes tiiiiiiiiiiiime

Typically does not handle temporal issues naturally - usually has to cheat by looking at successive snapshots

Relatively little additive knowledge

Successes

Evol Computation

Now a mainstream technique

Optimisation

Evol Robotics

Sims

"In principle" studies

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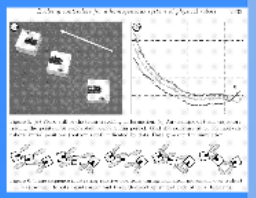

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Compare

Reason
Classical AI

Perception
Action
Loop

Action
(someone
else's job)

Classify
Neural
Networks

Real World

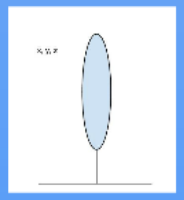
Perception
Action
Loop

Evol Robotics

Contrast

Compare

Reason
Classical AI



Perception
Action
Loop

Action
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Classify
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Evol Robotics

Contrast

$x^2 + y^2 = z^2$

Rational Thought

"What differentiates
Humans from other animals"

Disembodied Logic
Rigidly constrained worlds
Little/no noise
Chess

Adaptive Behaviour
Robust to changing context

4,000 kms each way
3 or 4 generations/cycle
Weighs a few milligrams
magnetic sense, sun compass
circadian clock, photoreceptors,
smell ... ...

"AI always prom

Once delivered

Any suff
indistin

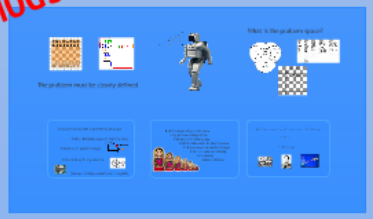
Perspectives on AI

Inman Harvey

Classical AI

Origins

Methods



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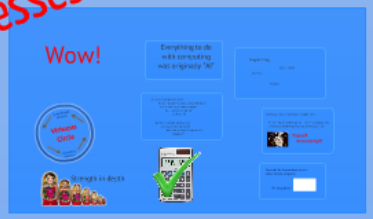

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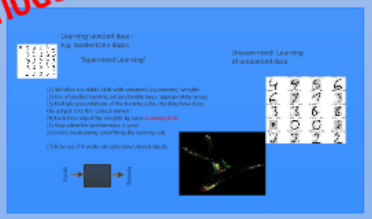
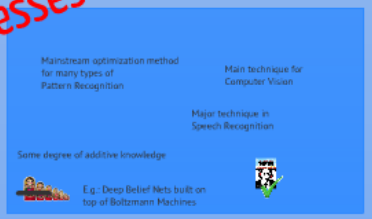
Origins

Methods



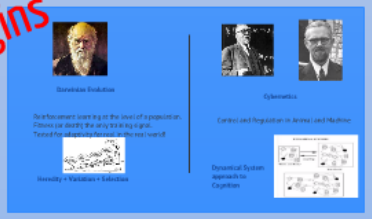
Successes



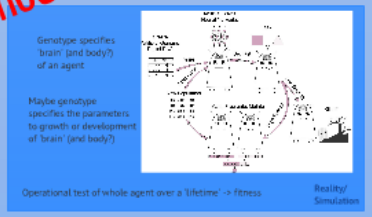
Failures

Evolutionary Robotics

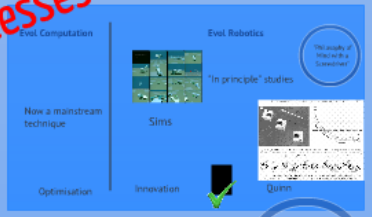
Origins



Methods



Successes



Failures