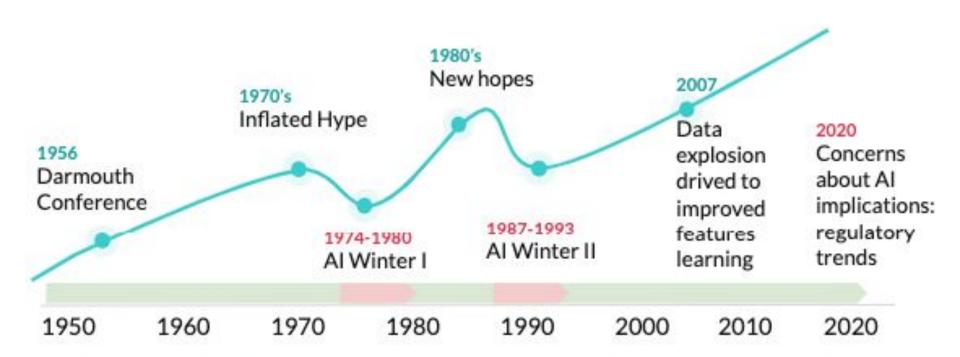
# Artificial Intelligence

Kushal Shah @ Sitare



# Eye-catching advances in some AI fields are not real

When tuned up, old algorithms can match the abilities of their successors

27 MAY 2020 · BY MATTHEW HUTSON

Researchers are waking up to the signs of shaky progress across many subfields of AI. A 2019 meta-analysis of information retrieval algorithms used in search engines concluded the "high-water mark ... was actually set in 2009." Another study in 2019 reproduced seven neural network recommendation systems, of the kind used by media streaming services. It found that six failed to outperform much simpler, nonneural algorithms developed years before, when the earlier techniques were fine-tuned, revealing "phantom progress" in the field. In another paper posted on arXiv in March, Kevin Musgrave, a computer scientist at Cornell University, took a look at loss functions, the part of an algorithm that mathematically specifies its objective. Musgrave compared a dozen of them on equal footing, in a task involving image retrieval, and found that, contrary to their developers' claims, accuracy had not improved since 2006. "There's always been these waves of hype," Musgrave says.

# Mastering the game of Go with deep neural networks and tree search

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The game of Go has long been viewed as the most challenging of classic games for artificial intelligence owing to its enormous search space and the difficulty of evaluating board positions and moves. Here we introduce a new approach to computer Go that uses 'value networks' to evaluate board positions and 'policy networks' to select moves. These deep neural networks are trained by a novel combination of supervised learning from human expert games, and reinforcement learning from games of self-play. Without any lookahead search, the neural networks play Go at the level of state-of-the-art Monte Carlo tree search programs that simulate thousands of random games of self-play. We also introduce a new search algorithm that combines Monte Carlo simulation with value and policy networks. Using this search algorithm, our program AlphaGo achieved a 99.8% winning rate against other Go programs, and defeated the human European Go champion by 5 games to 0. This is the first time that a computer program has defeated a human professional player in the full-sized game of Go, a feat previously thought to be at least a decade away.

#### Artificial Intelligence

Methods for computer systems to perform human tasks

#### **Machine Learning**

Mathematical models with specified structure learn to perform tasks from data

#### Deep Learning

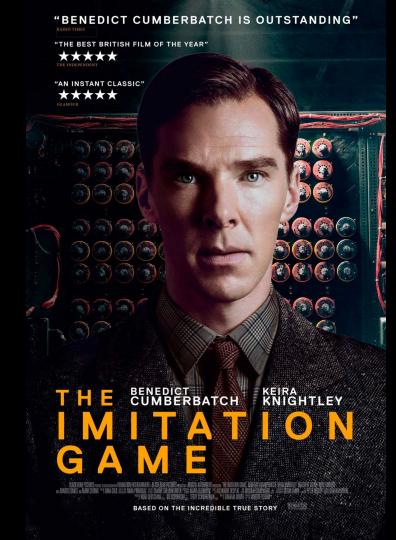
Neural networks with multiple specialized layers for encoding structural information

#### **Expert Systems**

Operate autonomously with human specified rules. (e.g. fuzzy logic)

#### Statistics

Foundational Techniques and Training Principles



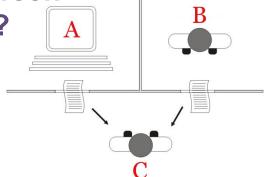
**Turing Test** 

[Alan Turing 1950]

Can humans tell the difference between machines and one of their kind?

**Turing Test** 

[Alan Turing 1950]



Can humans tell the difference between machines and one of their kind?

**Turing Test** 

[Alan Turing 1950]



Can humans tell the difference between machines and one of their kind?

**Turing Test** 

[Alan Turing 1950]



**Chinese Room Argument** 

[John Searle 1980]

Passing the Turing Test is not equivalent to Intelligence!

Intelligence measures an agent's ability to achieve goals in a wide range of environments. Intelligence is not really the ability to do anything in particular, rather it is a very general ability that affects many kinds of performance.

[S. Legg and M. Hutter 2007]

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[S. Legg and M. Hutter 2007]

Turing Test and several other measures of Intelligence conflate computing power with Intelligence!

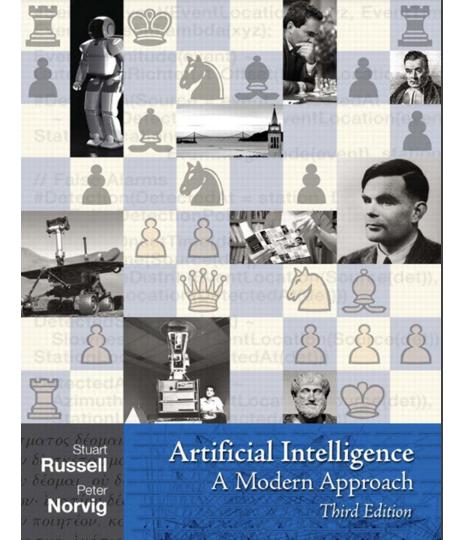
# ~ Edsger Dijkstra ~

The question of whether Machines Can Think . . .

is about as relevant as the question

of whether Submarines Can Swim.

















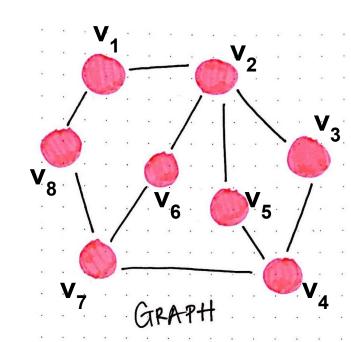






GoodWorkLabs Technology Superstars

# Graph

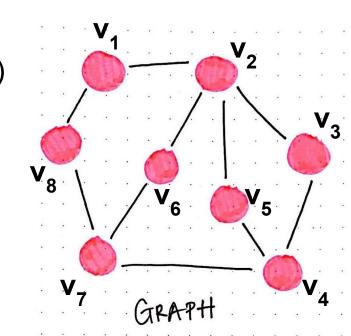


# **Graph G(V, E)**

- Finite, non-empty set of vertices or nodes, V(G)

Finite, possibly empty set of edges, E(G)

Elements of E(G) are pairs of vertices :  $(v_1, v_2)$ ,  $(v_2, v_6)$ , and so on.



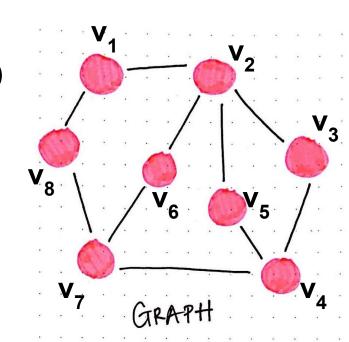
# **Graph G(V, E)**

Which nodes in this graph are adjacent?

- Finite, non-empty set of vertices or nodes, V(G)

Finite, possibly empty set of edges, E(G)

Elements of E(G) are pairs of vertices :  $(v_1, v_2)$ ,  $(v_2, v_6)$ , and so on.



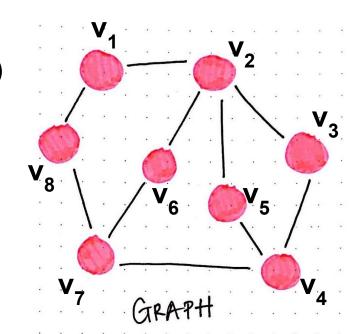
# **Graph G(V, E)**

What is the degree of vertex v<sub>2</sub>?

- Finite, non-empty set of vertices or nodes, V(G)

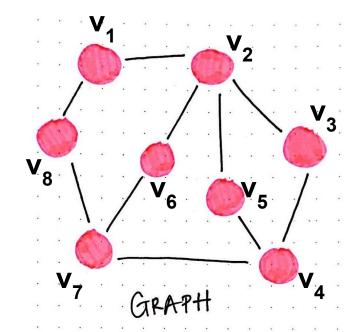
Finite, possibly empty set of edges, E(G)

Elements of E(G) are pairs of vertices :  $(v_1, v_2)$ ,  $(v_2, v_6)$ , and so on.



# **Directed Graph** $(v_1, v_2) \neq (v_2, v_1)$

Undirected Graph 
$$(v_1, v_2) = (v_2, v_1)$$

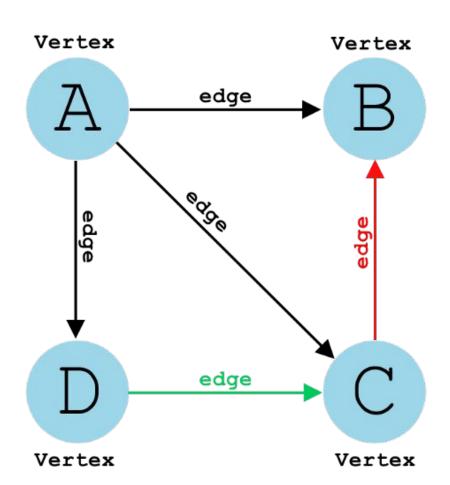


## **Directed Graph**

$$(v_1, v_2) \neq (v_2, v_1)$$

## **Undirected Graph**

$$(v_1, v_2) = (v_2, v_1)$$



# **Directed Graph**

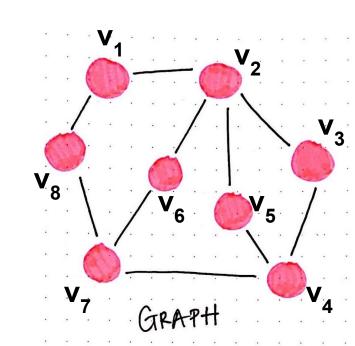
$$(v_1, v_2) \neq (v_2, v_1)$$

# **Undirected Graph**

$$(v_1, v_2) = (v_2, v_1)$$

## **Complete Graph**

A graph that has the maximum number of edges



# **Directed Graph**

$$(\mathsf{v}_1,\mathsf{v}_2) \neq (\mathsf{v}_2,\mathsf{v}_1)$$

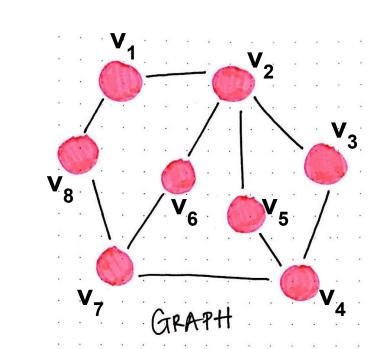
## **Undirected Graph**

$$(v_1, v_2) = (v_2, v_1)$$

# **Complete Graph**

A graph that has the maximum number of edges

How many edges will this graph have if we make it complete?



## Simple Path

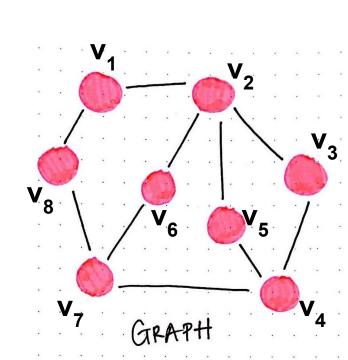
Path in which all vertices, except possibly the first and last are distinct

### Cycle

Simple path in which the first and last vertices are the same

#### **Connected Vertices**

Vertices between which there is a path



What is a connected graph?

## **Simple Path**

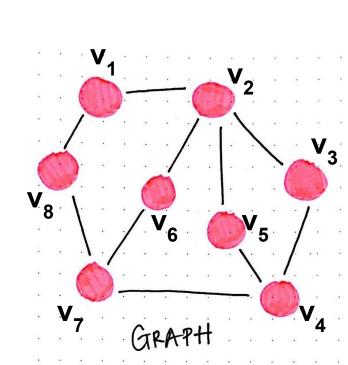
Path in which all vertices, except possibly the first and last are distinct

### Cycle

Simple path in which the first and last vertices are the same

#### **Connected Vertices**

Vertices between which there is a path



What is the difference between connected and complete graph?

## **Simple Path**

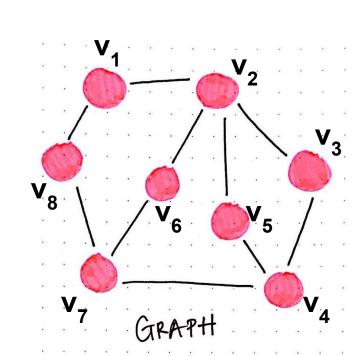
Path in which all vertices, except possibly the first and last are distinct

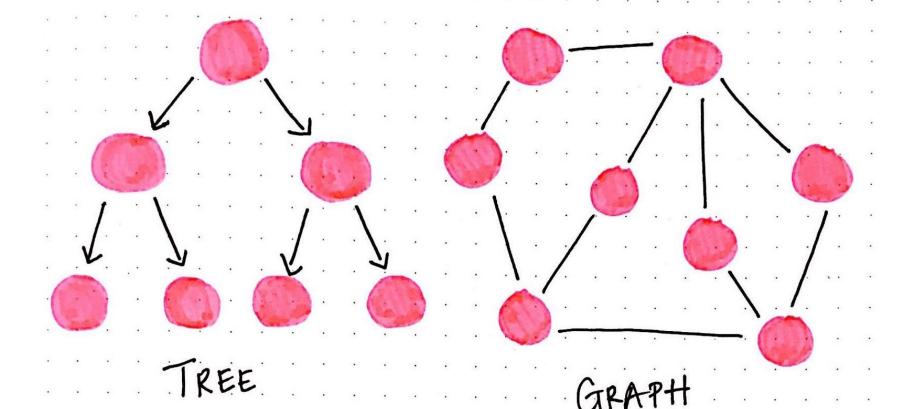
### Cycle

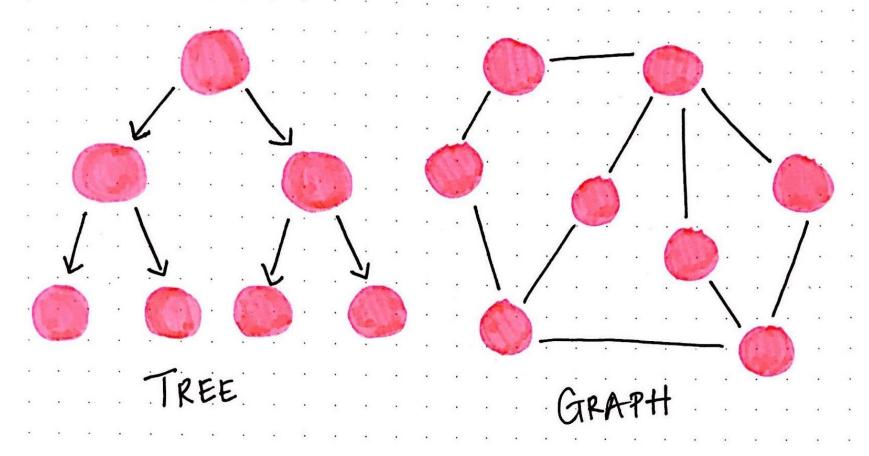
Simple path in which the first and last vertices are the same

#### **Connected Vertices**

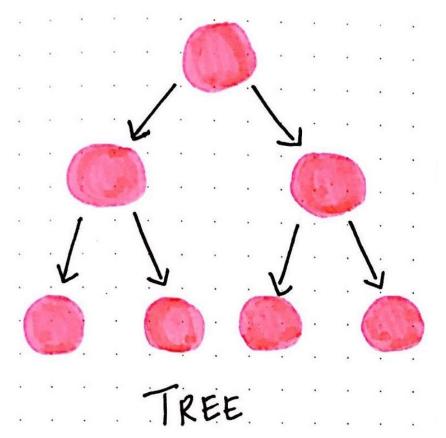
Vertices between which there is a path



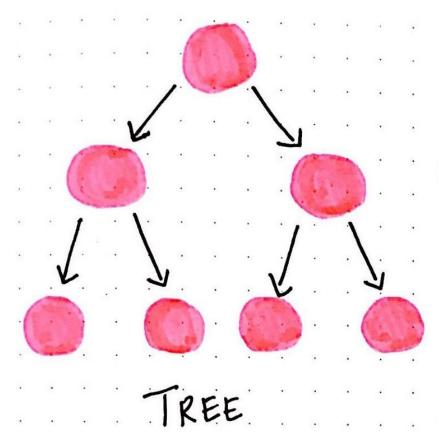




A **tree** is a directed acyclic graph [DAG] that is connected and in which each node has only one parent.



What is the in-degree of a node in this tree?



What is the out-degree of a node in this tree?



# **Adjacency Matrix**

```
graph = [[0, 1, 2],
         [2, 0, 5],
         [4, 5, 0]
```

## **Adjacency List**

$$A \rightarrow [(B, 4), (C, 1)]$$

## **Edge List**

```
graph = [(C, A, 4), (A, C, 1), (B, C, 6),
(A, B, 4), (C, B, 1), (C, D, 2)]
```