STEVENS
INSTITUTE OF TECHNOLOGY
1870

PEP 559
Machine Learning in Quantum Physics

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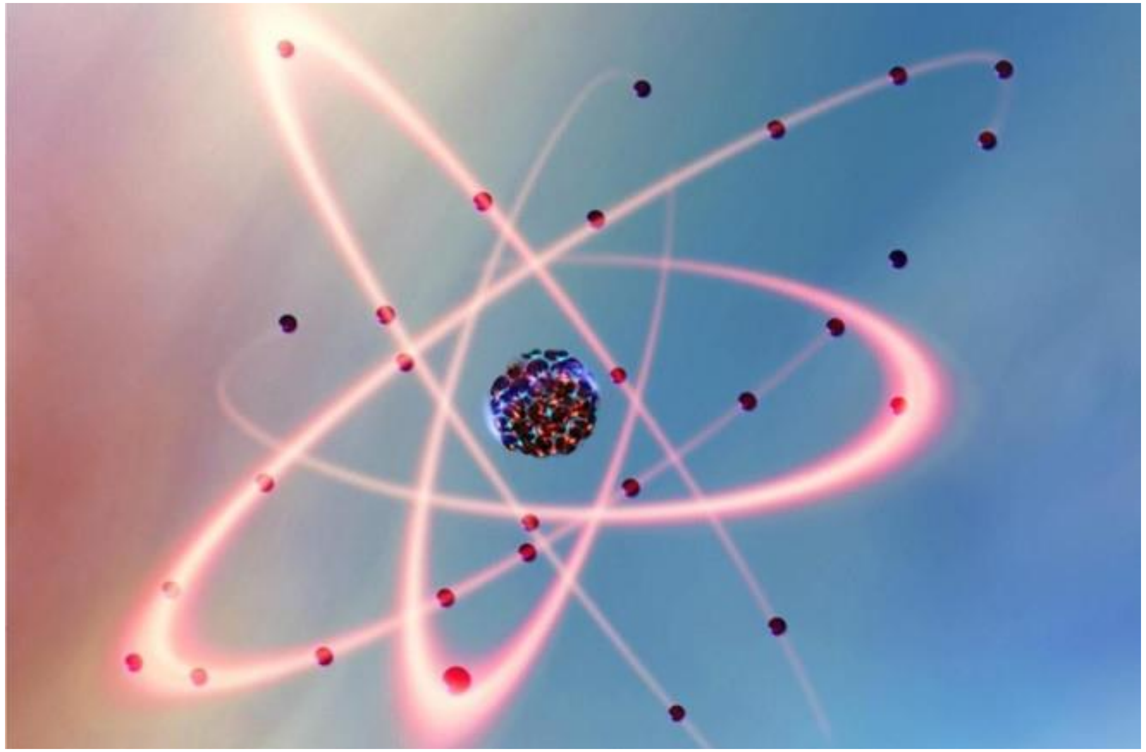
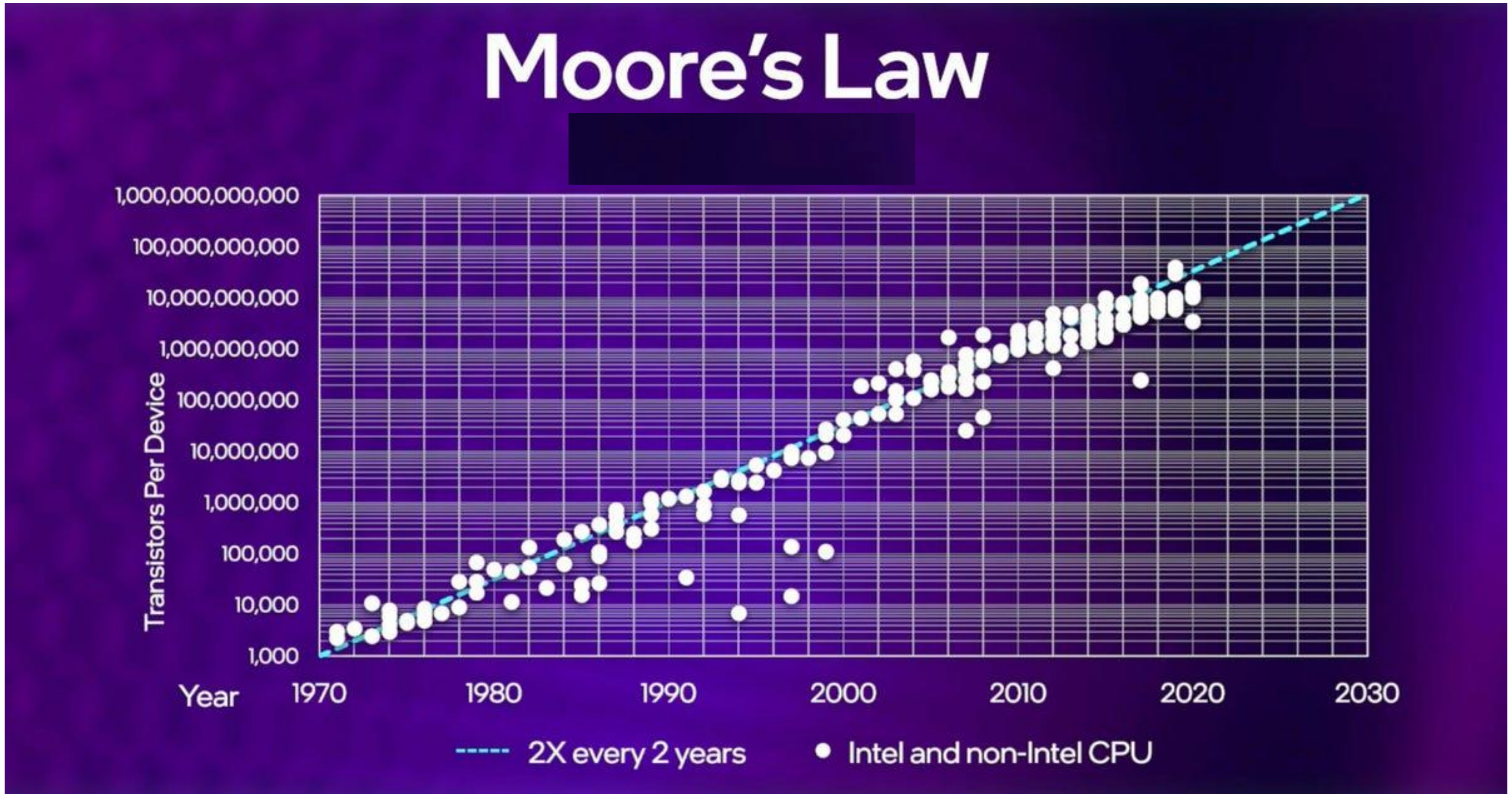
Spring 2026

Why Quantum?

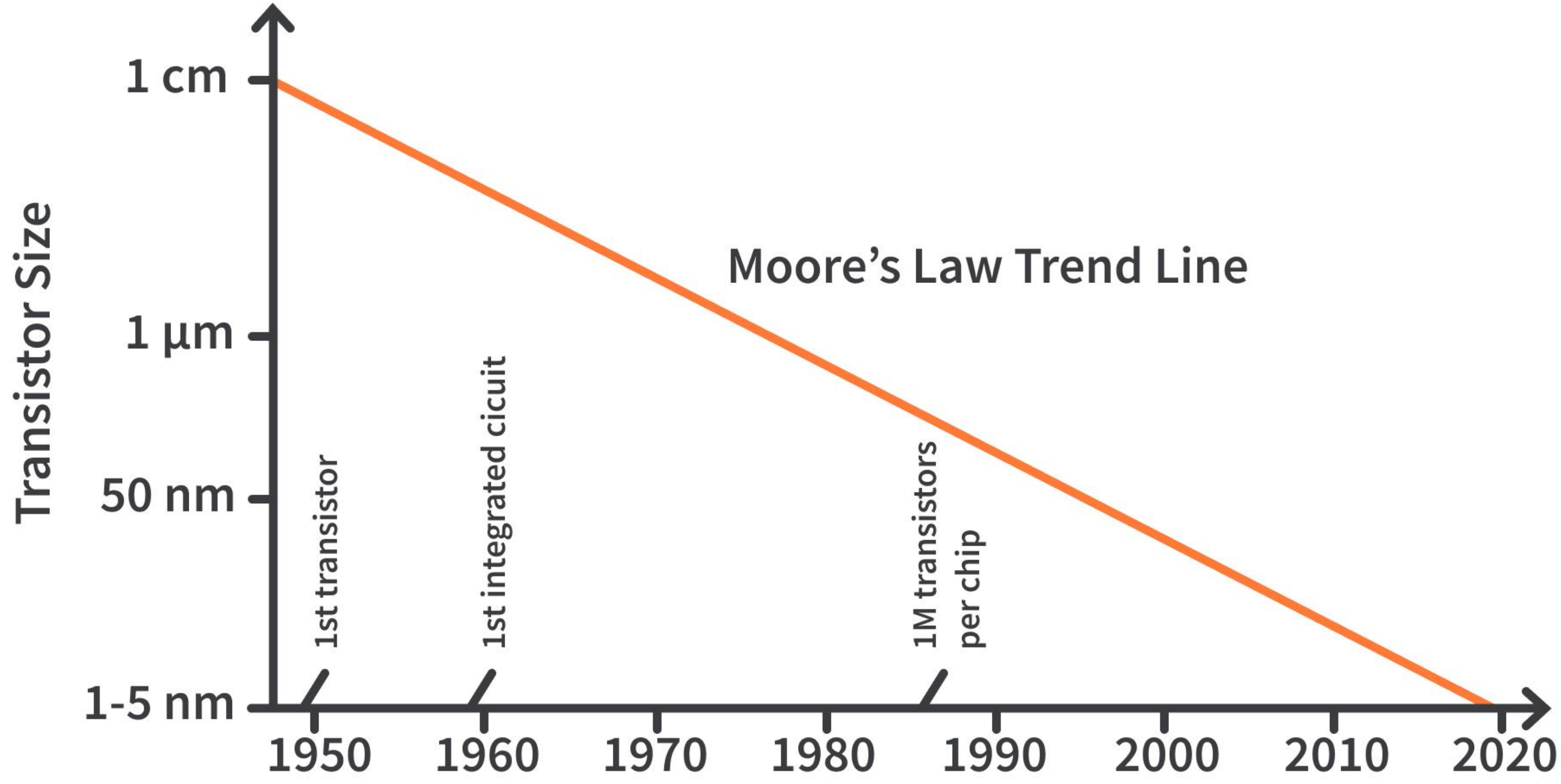
Because **conventional technologies** become incapable to address some **big challenges**





- The number of transistors on a chip doubles every two years
- Will this continue? What happens if the size of the transistor is too small?

Need new materials at the nano or even single-atom level which are governed by Quantum Mechanics

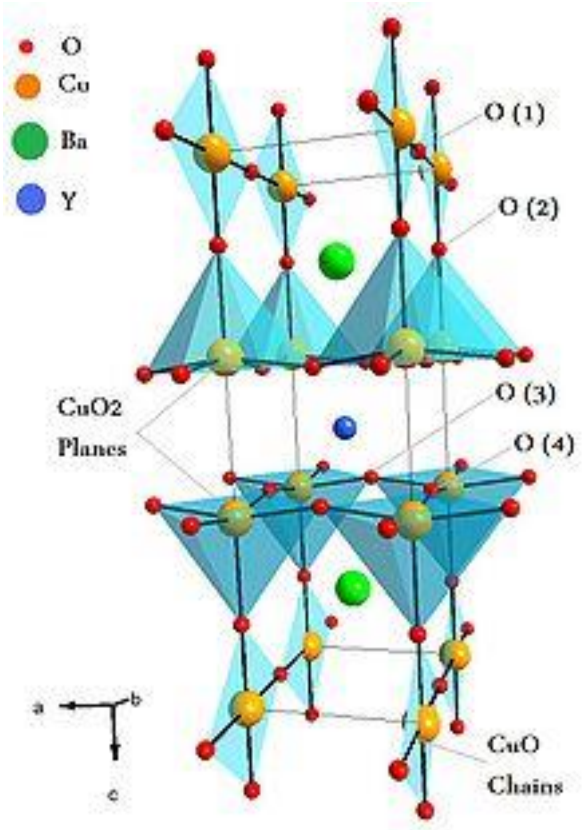


Traveling salesman problem

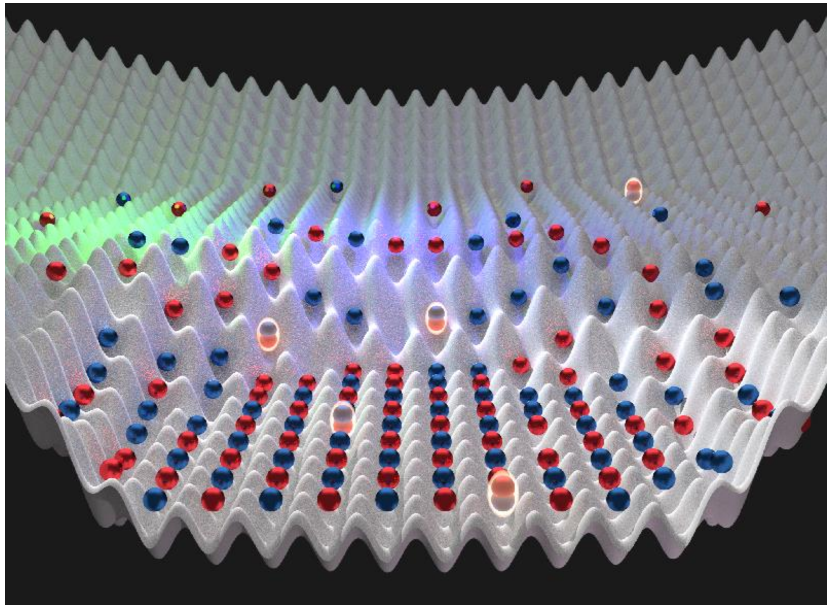
- The salesman must travel to all cities once before returning home
- The distance between any two cities is given, and is assumed to be the same in both directions
- Objective – minimize the total distance to be traveled

Quantum computer may solve problems that are hard or impossible on conventional classical computers

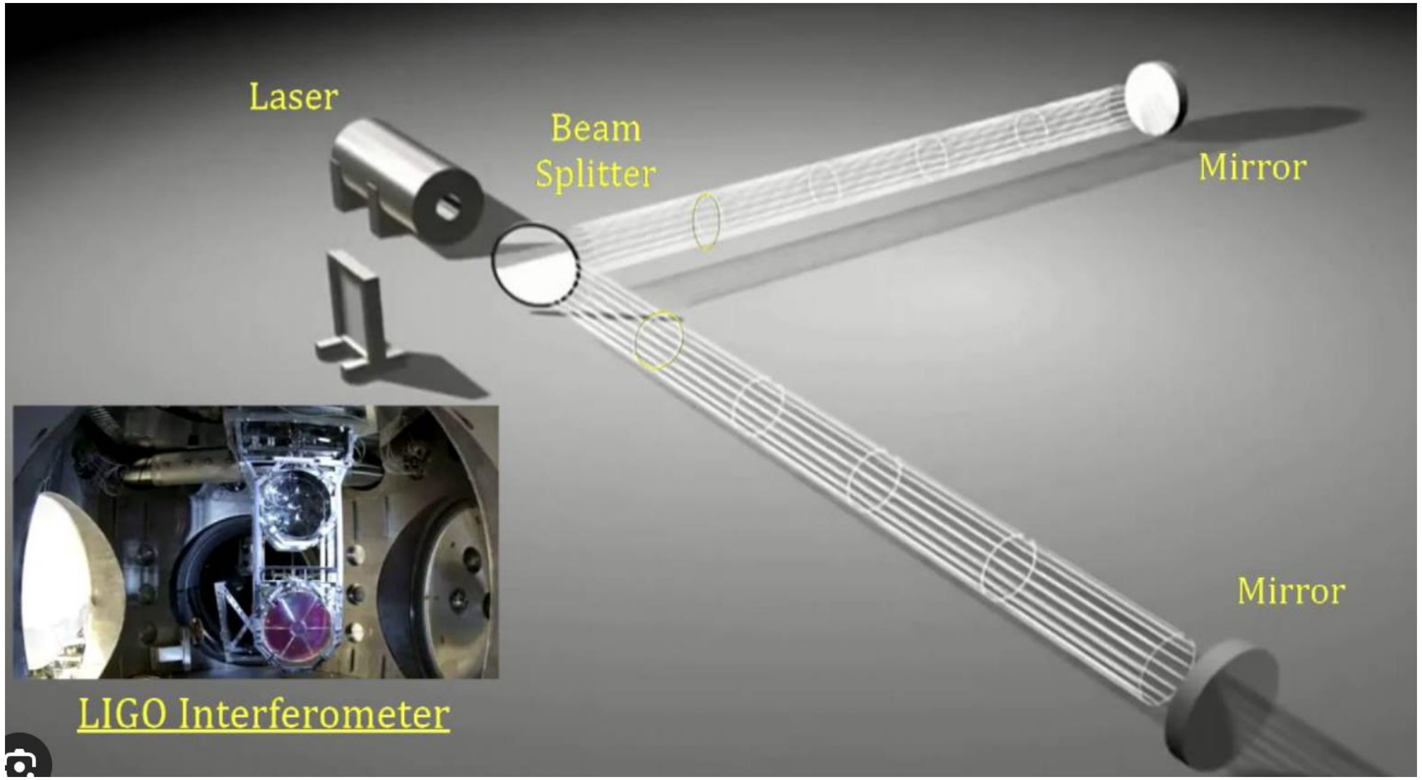
High-temperature superconductivity

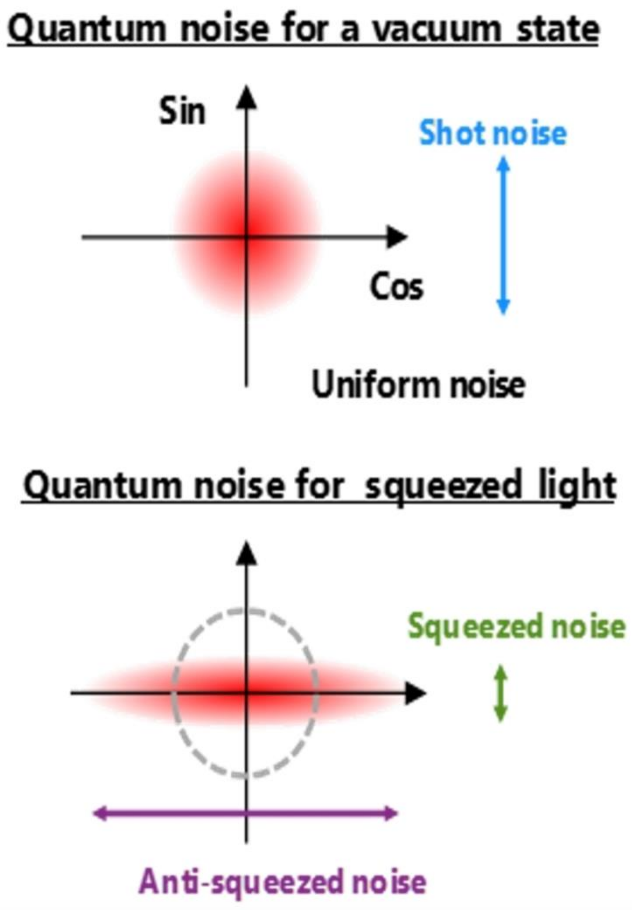


- Many-body problem – difficult to solve with classical computers
- We can make a quantum simulator: a controllable synthetic quantum system that mimics the behavior of real complex quantum material

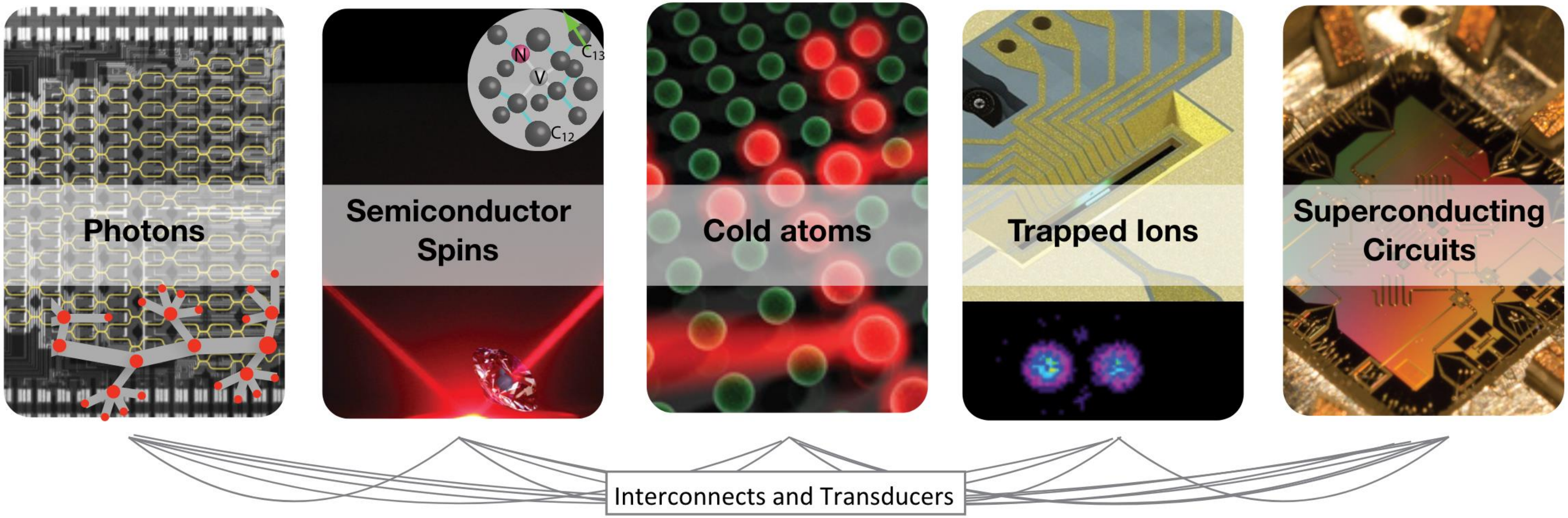


Quantum sensing





Leading physical platforms

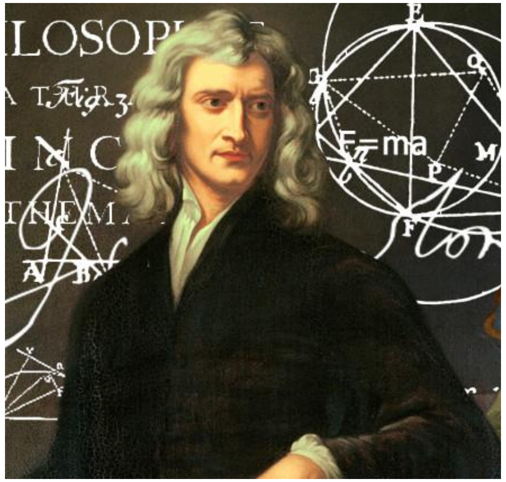


To connect these platforms often requires the development of transducers to photonic states, which can travel long distance with little decoherence

An overview of the historical development of quantum physics

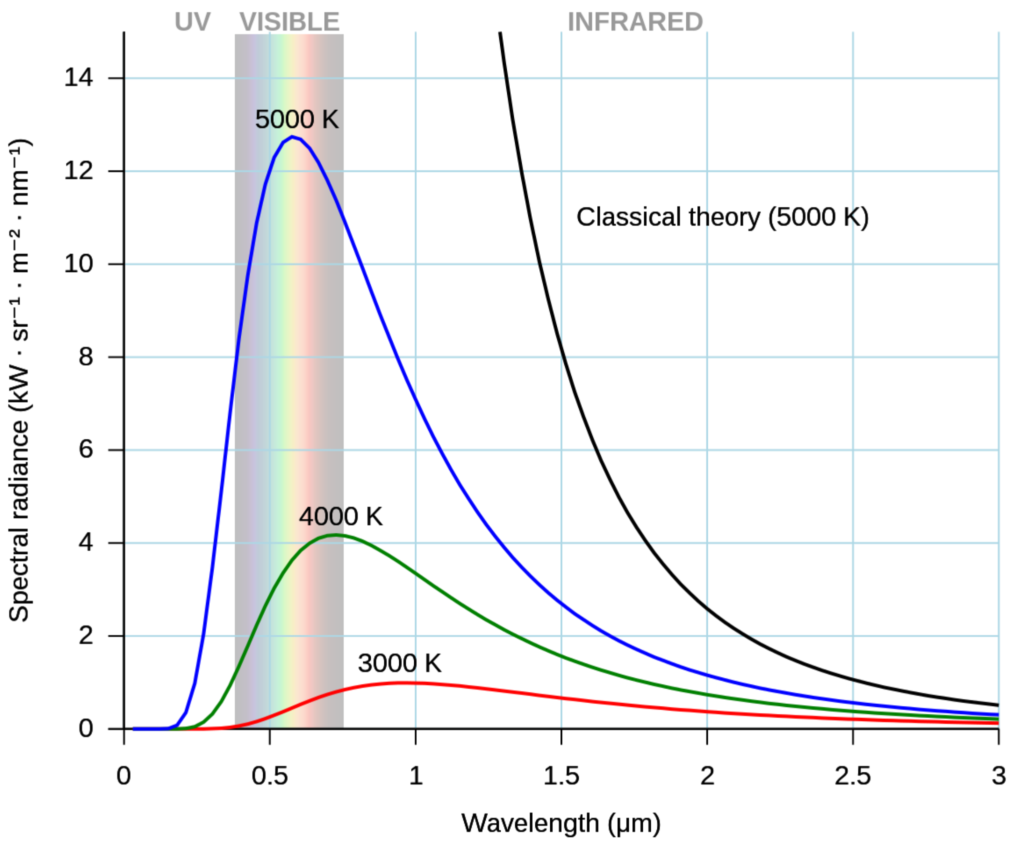
Some contradictions

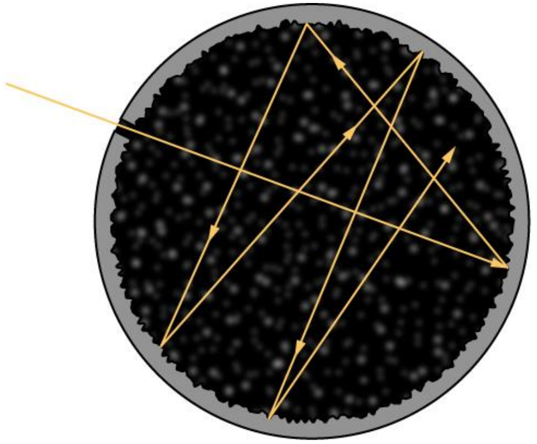
- At the end of 19th century, despite the tremendous achievements of classical physics (Newtonian mechanics, Maxwell's electrodynamics, Boltzman's statistical physics), people found that a series of phenomena and experiments could not be understood with classical physics



Black-body radiation

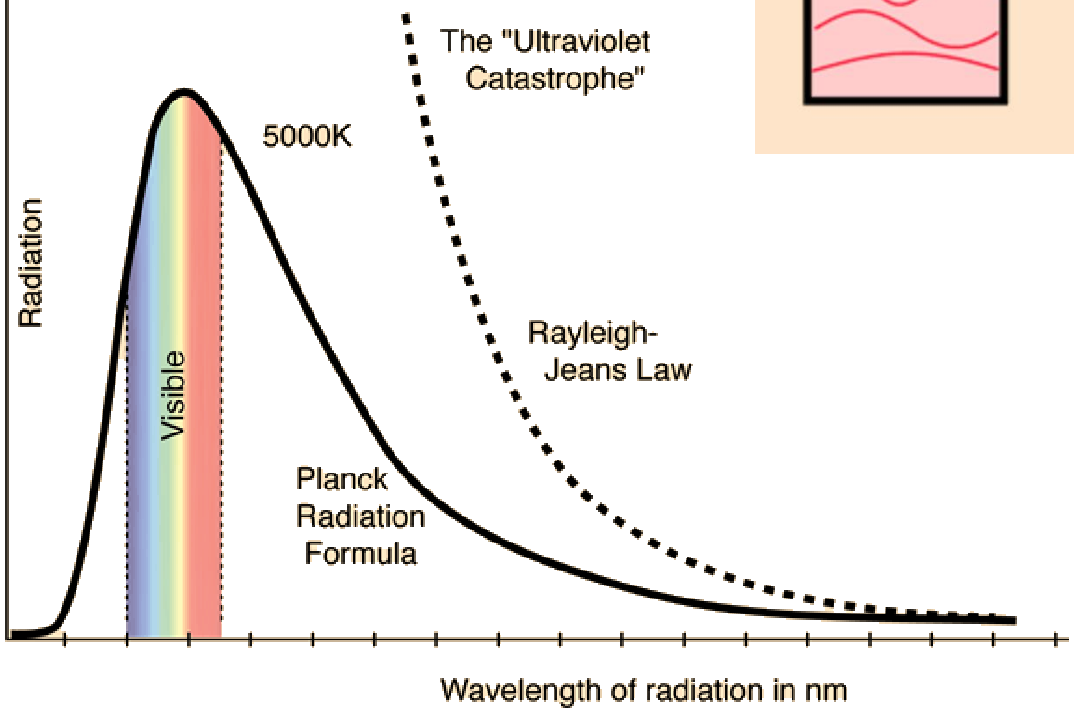
Ultraviolet Catastrophe



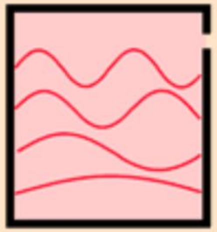


Discrepancy between experimentally measured blackbody radiation (blue) and the prediction based on classical theory (black) at high frequency (or longer wavelength) regime

The birth of Quantum Physics (1900)



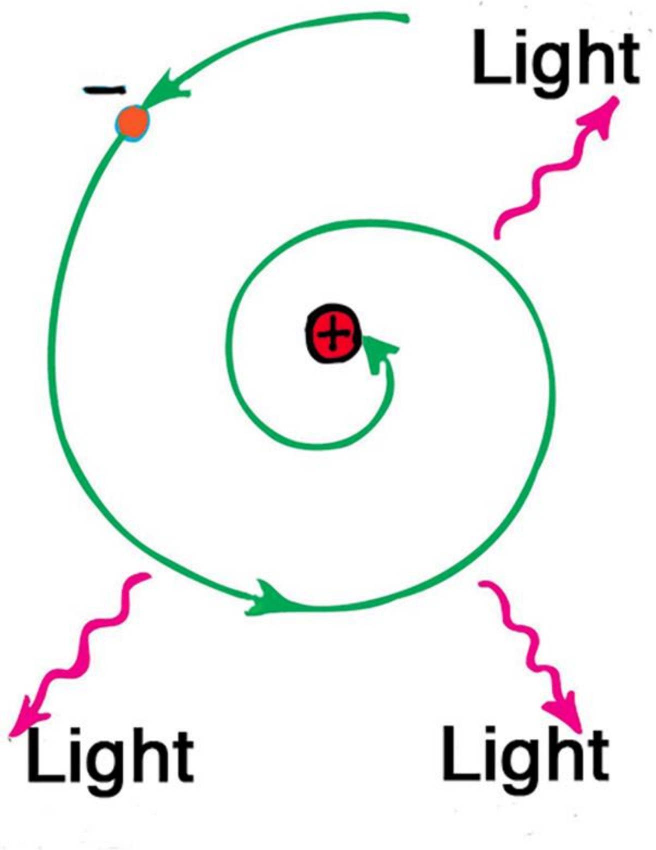
Radiation modes in a hot cavity provide a test of quantum theory



	#Modes per unit frequency per unit volume	Probability of occupying modes	Average energy per mode
CLASSICAL	$\frac{8\pi\nu^2}{c^3}$	Equal for all modes	kT
QUANTUM	$\frac{8\pi\nu^2}{c^3}$	Quantized modes: require $h\nu$ energy to excite upper modes, less probable	$\frac{h\nu}{e^{\frac{h\nu}{kT}} - 1}$

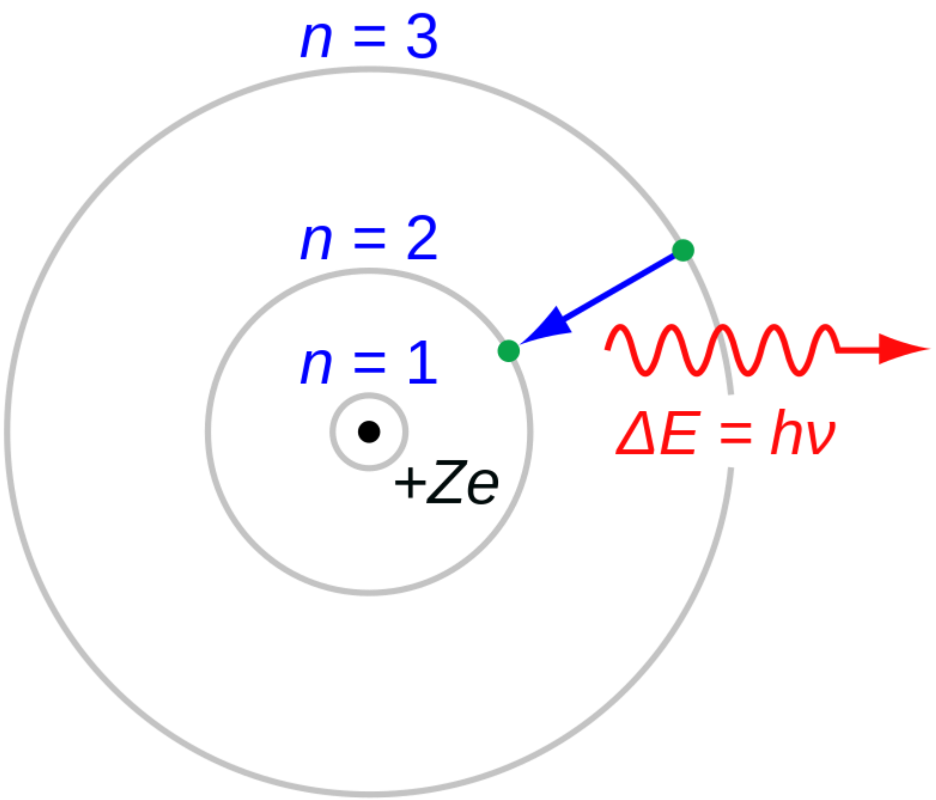
Planck

Stability of atoms



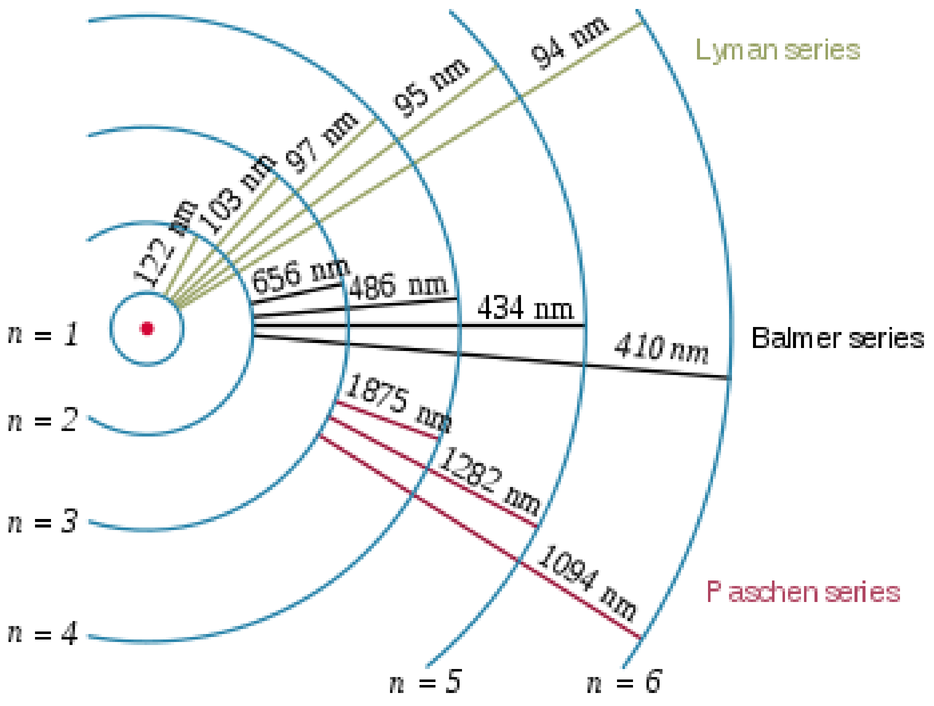
- According to classical physics, an electron orbiting around a nucleus emits radiation continuously.
- So, it should spiral into the nucleus in a short time
- i.e., atoms cannot exist!

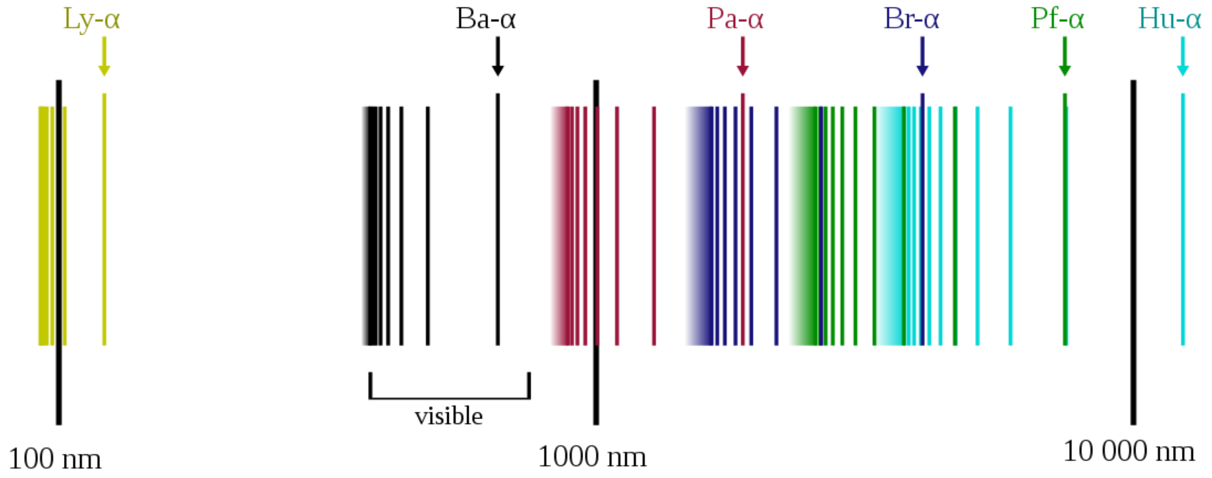
Bohr's atomic model (1915)



- Electrons orbit the nucleus in circular orbits, forming electron shells
- Electrons do not radiate
- Electrons gain energy to move to higher orbits or lose energy to drop to lower orbits, by absorbing or emitting photons

Spectrum of Hydrogen atoms

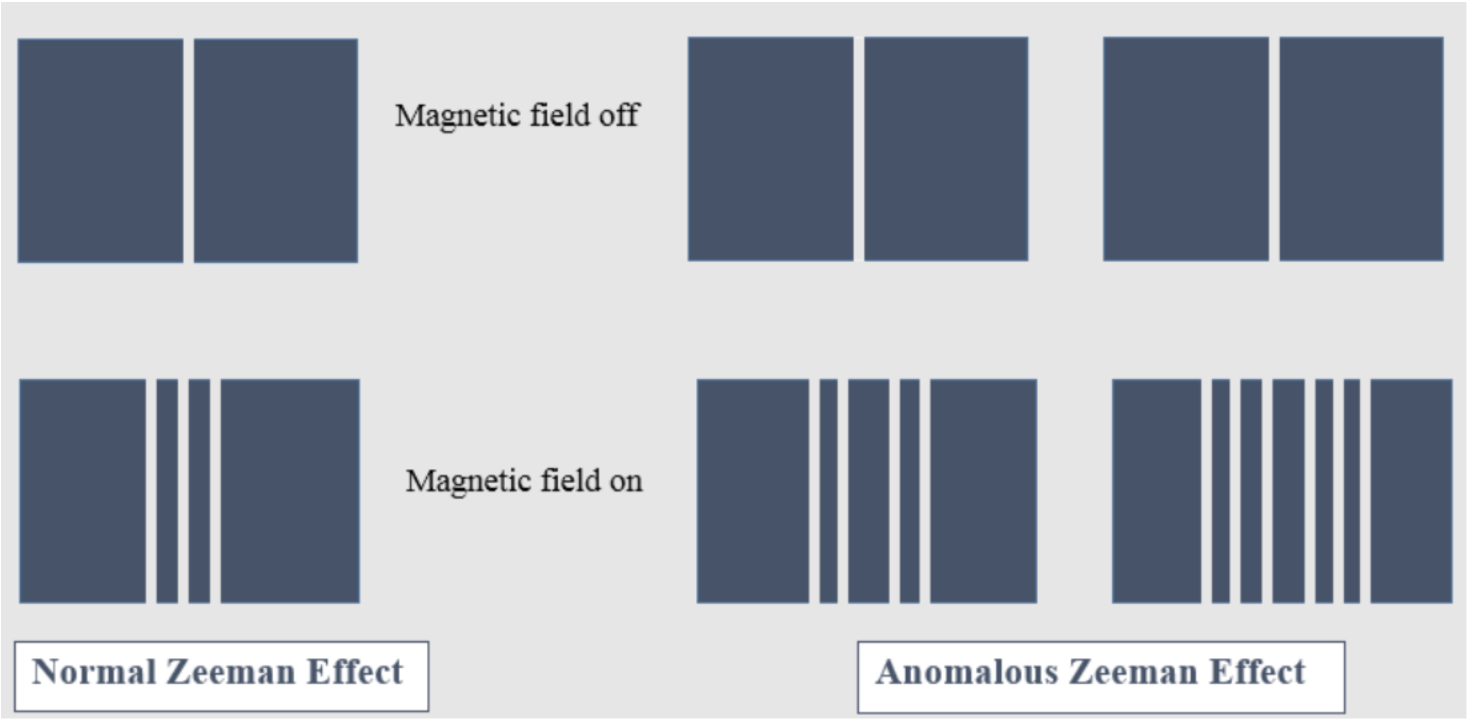




- It can be explained by Bohr’s model. However, Bohr’s model is not enough for other effects.

The normal and anomalous Zeeman effects

- 1896, Dutch physicist Peter Zeeman
- Splitting of spectral liens emitted by atoms, when kept in a strong magnetic field



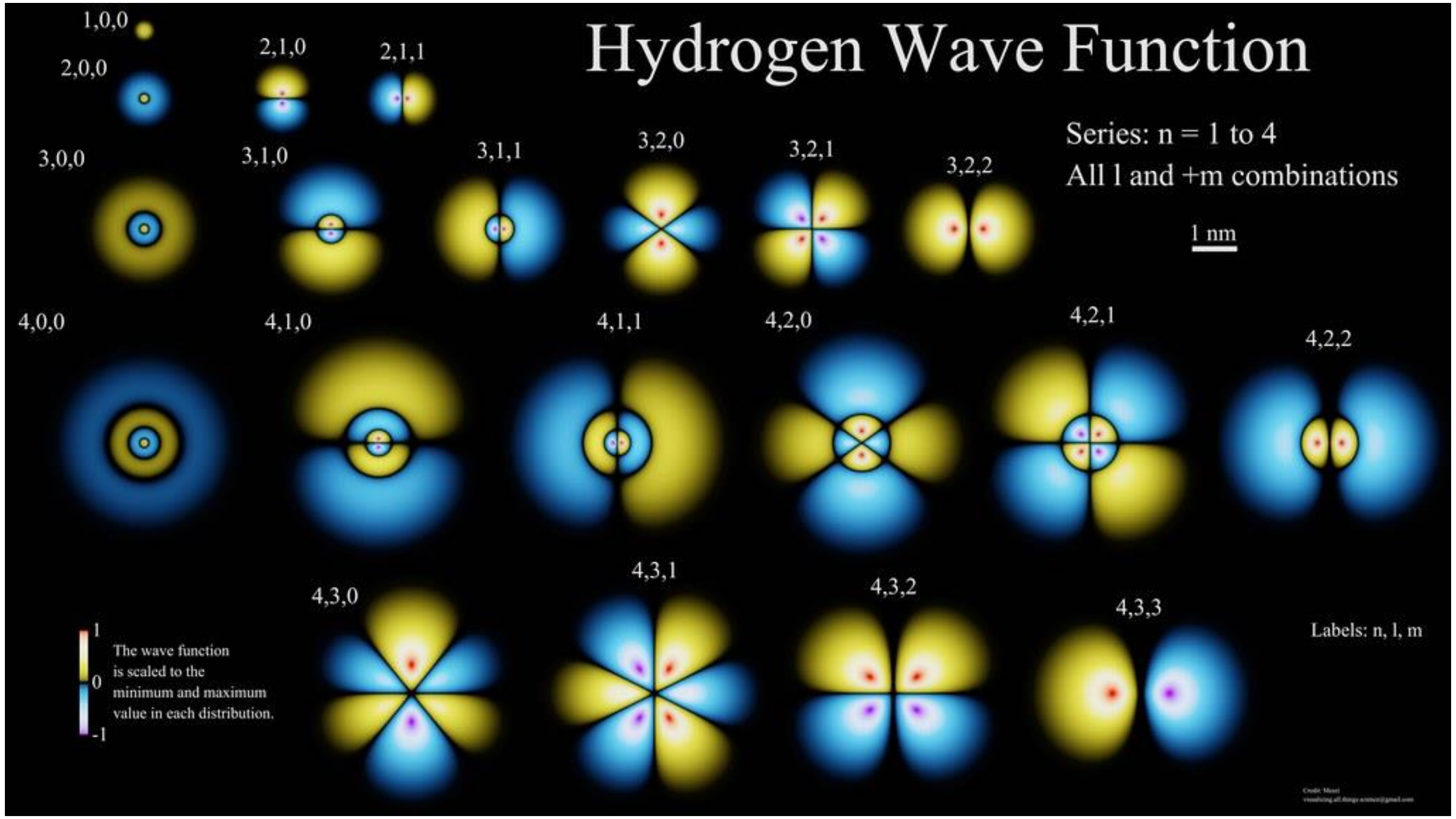
- The normal Zeeman splitting is due to orbital angular momentum [l]
- To understand the anomalous Zeeman splitting, we need to introduce Spin [S]

Schrodinger equation (1925)

- A more complete description of the atoms requires the solution of Schrodinger equation

$$i\hbar\frac{\partial}{\partial t}\Psi(x,t) = \left[-\frac{\hbar^2}{2m}\frac{\partial^2}{\partial x^2} + V(x,t)\right]\Psi(x,t).$$

$$-\frac{\hbar^2}{2m}\nabla^2\psi + V\psi = E\psi$$



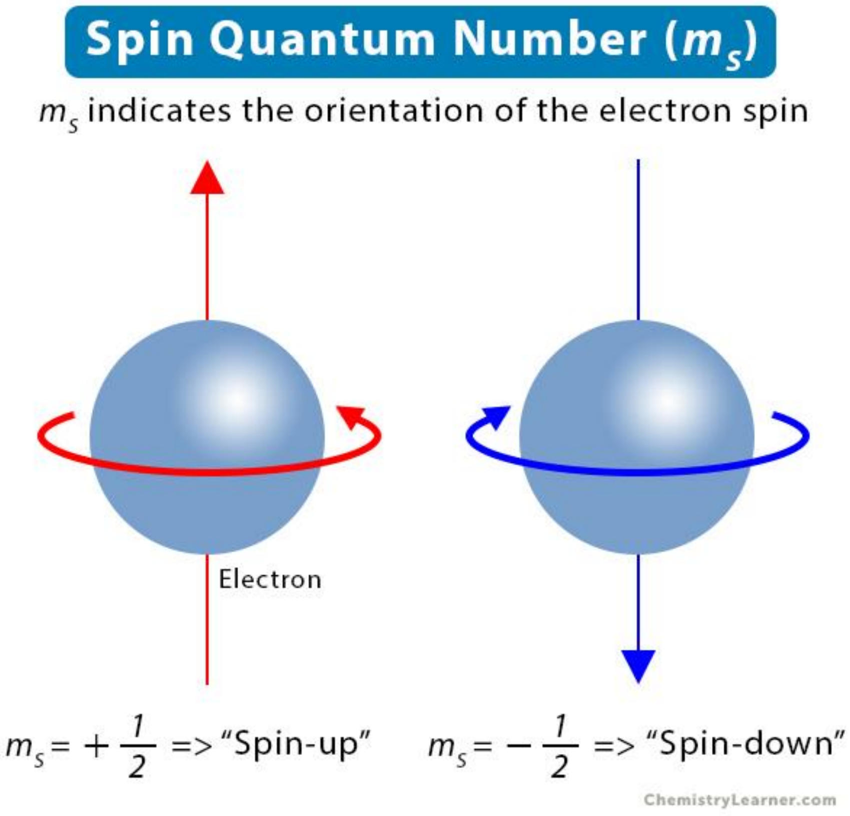
- Each orbit is characterized by three quantum numbers (n, l, m)

n: principal quantum number, l: orbital angular momentum quantum number, m: magnetic quantum number.

- The energy level only depends on n (degenerate levels) without B.

Spin angular momentum

- Electrons have another degree of freedom



$$(n, l, m_l, s, m_s)$$

Two major consequences

1. Fine structure
2. Anomalous Zeeman splitting

De Broglie's wavelength for matter wave (1923)

Wave - particle Duality.

Waves $\longrightarrow$ **could behave as particles(Photons of light).**

Planck

Similarly,

Matter/Particles (Electron) $\longrightarrow$ **could behave as a wave.**

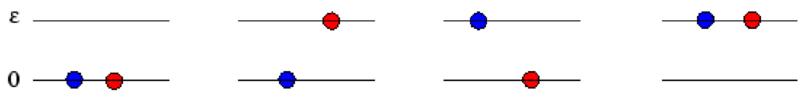
$$\lambda = \frac{h}{p}.$$

To show the wave nature of the particles, we need to reduce the momentum → That's why **quantum interference effect of matter waves** usually appears at low temperature

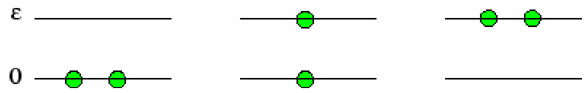
Bose and Einstein statistics (1924)

- Photons
- Some atoms (e.g., Helium 4)

- At T=0, they can stay at the lowest energy state to form the ground state

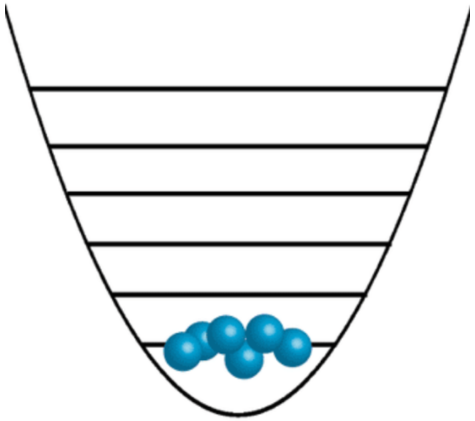


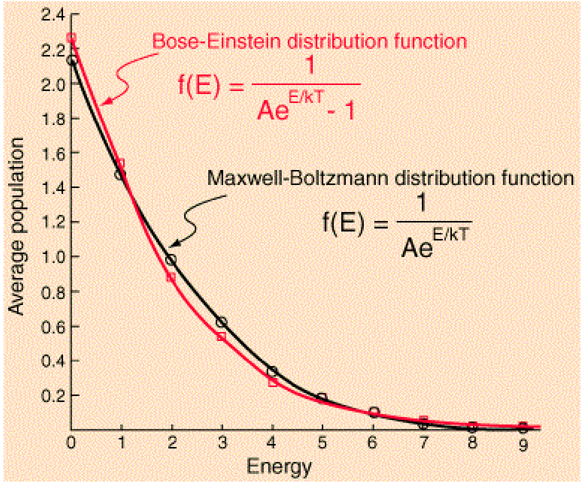
Distinguishable particles



Indistinguishable particles

Bosons



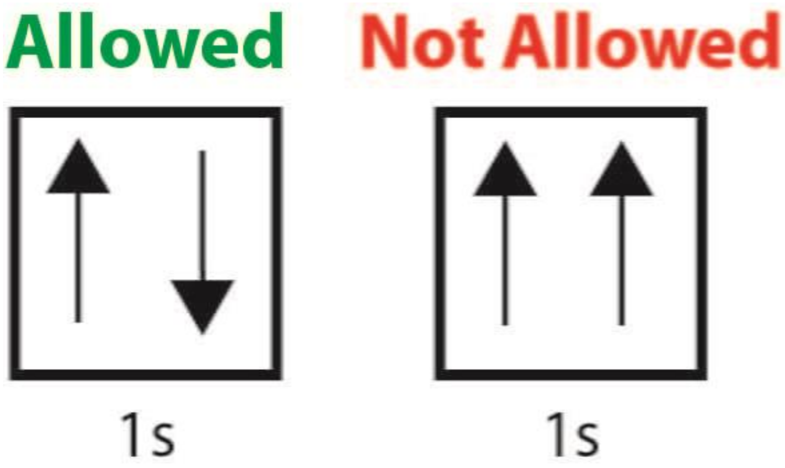


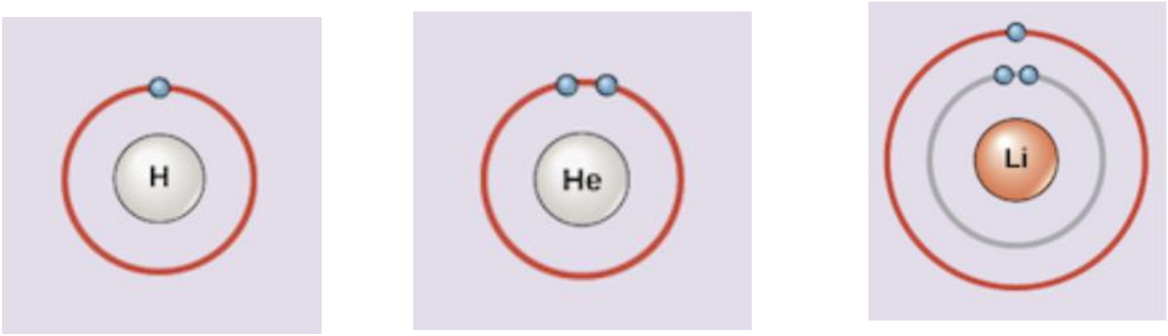
Bosons prefer to stay in the low energy states at low temperature, with the average population much higher than that predicted from Boltzman distribution → leading to the possibility of "**Bose-Einstein condensation**"

Pauli's exclusion principle (1924)

- Electrons
- Some atoms (e.g., Heliium 3)

No two particles can stay in the **same** quantum state. There must be a different quantum number to distinguish their quantum states





Heisenberg, Born, Jordan's matrix mechanics (1925)

Werner Heisenberg (1901-1976, German)

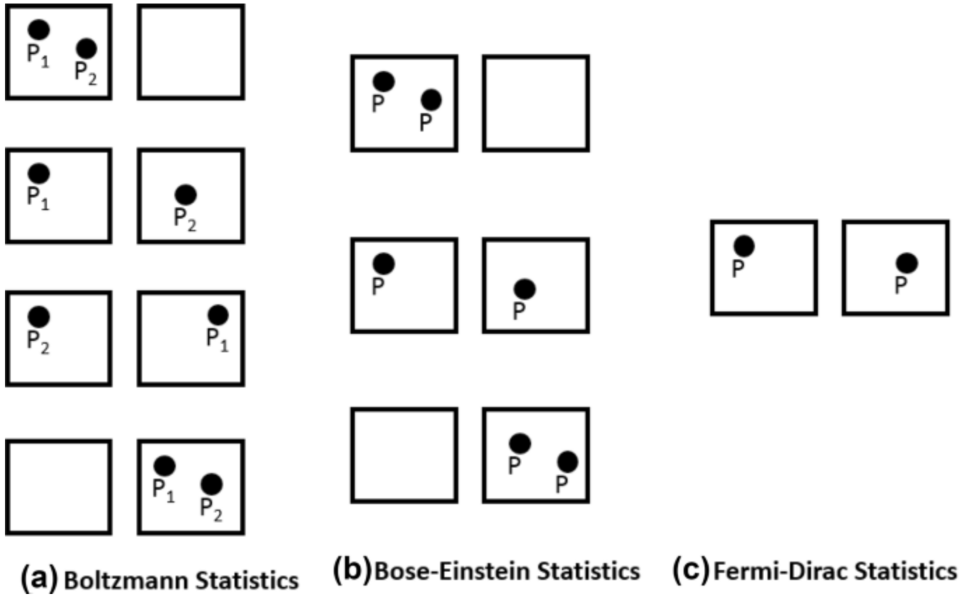
Nobel Prize: 1932

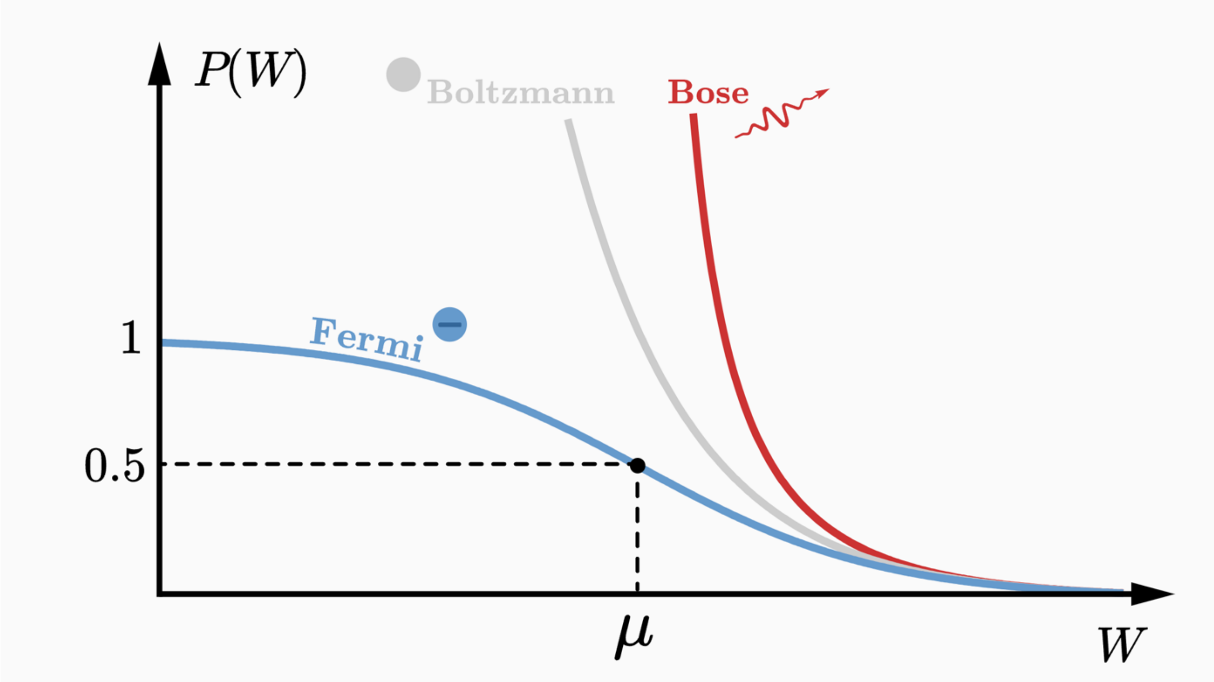
Matrix Mechanics:

Matrices: $\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$ $\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$

p *and* ***x*** *are represented as matrices of infinite dimension*

Fermi and Dirac distribution (1926)

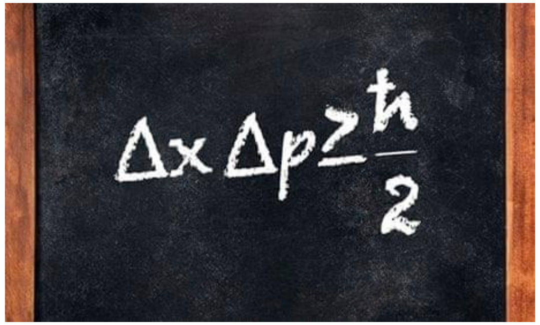


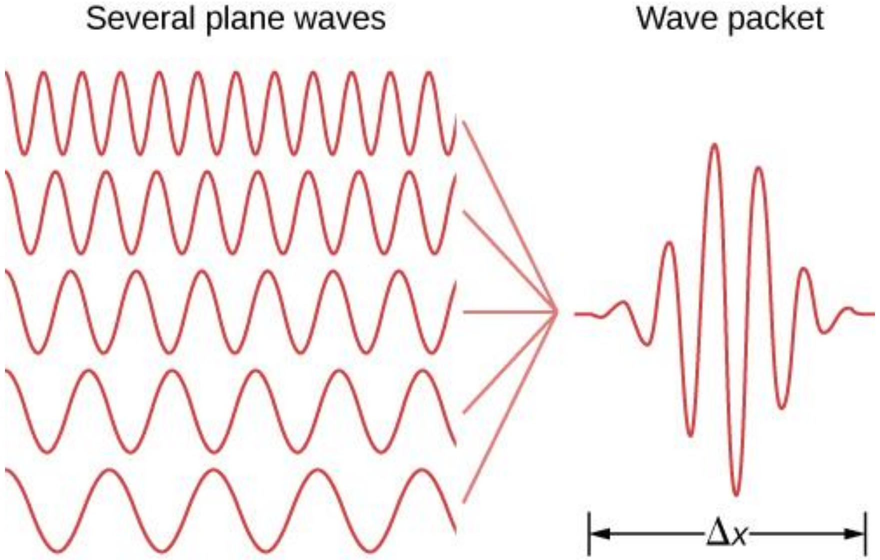


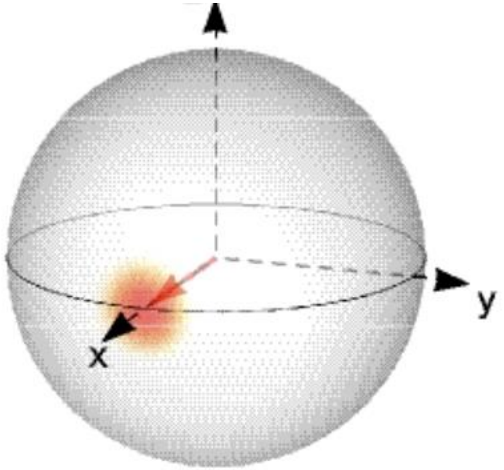
- At finite T, they prefer to repel each other

Heisenberg's uncertainty principle (1926)

- One cannot simultaneously determine the position and momentum of a particle
- Closely related to the particle-wave duality







$$[S_x, S_y] = i\hbar S_z$$

$$[S_y, S_z] = i\hbar S_x$$

$$[S_z, S_x] = i\hbar S_y$$

Schrodinger's wave equation (1926)

- A few months after Heisenberg

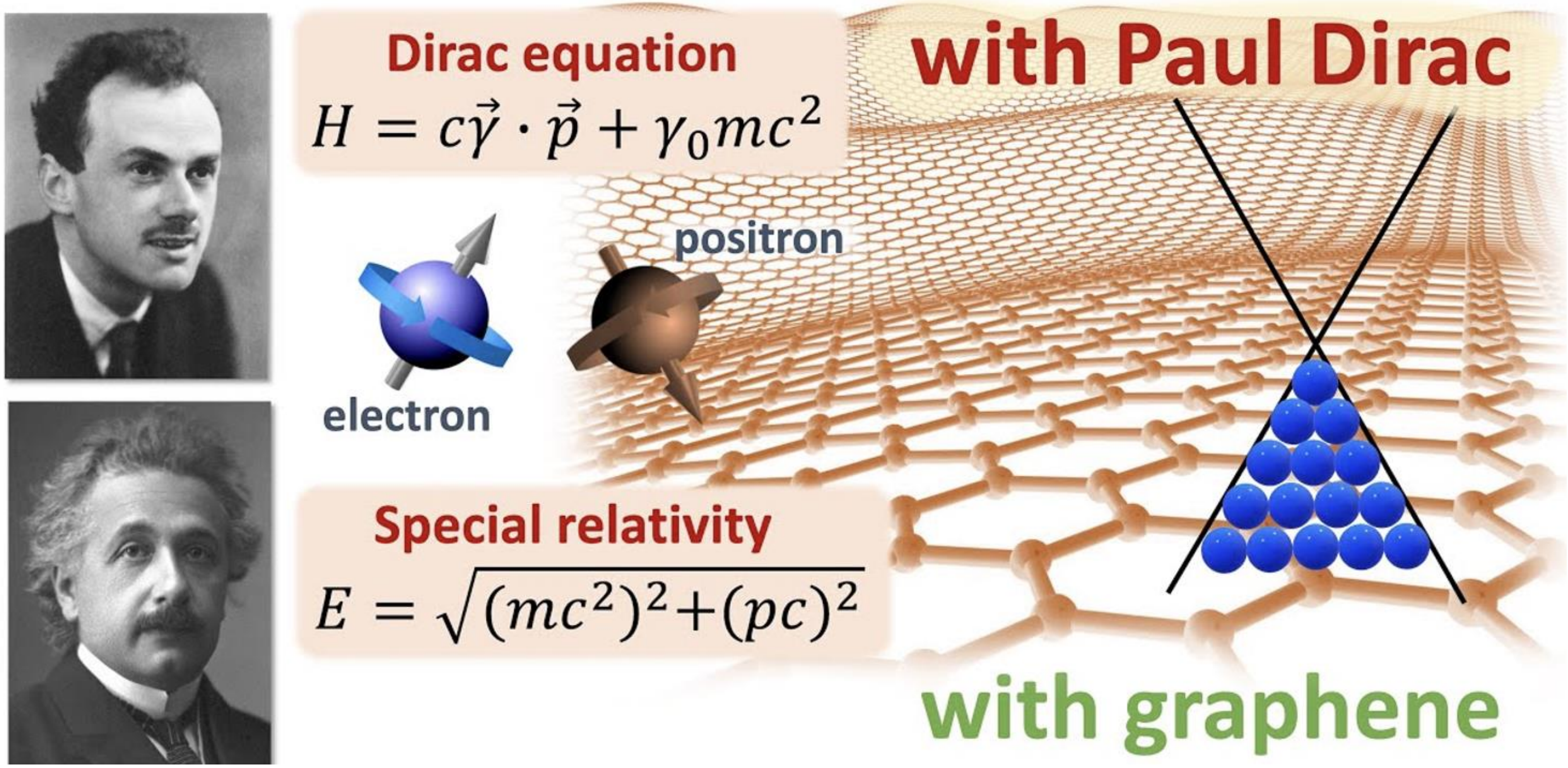
$$\hat{p} \to -i\hbar\vec{\nabla}$$

The state of particle is represented by a wave function which satisfies

$$i\hbar\frac{\partial}{\partial t}\Psi(\vec{r},t) = H\Psi(\vec{r},t)$$

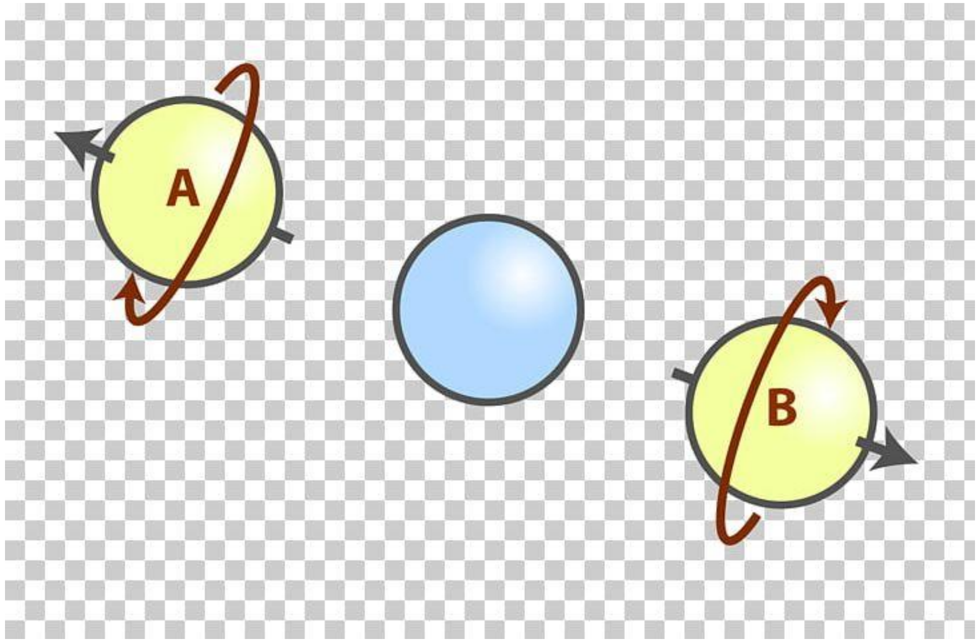
- **Born** and **Dirac** proved that the theories of Heisenberg and Schrodinger are in fact equivalent

Dirac's relativistic equation (1928)



- 1932, Anderson found positron

Einstein, Podolsky, Rosen's paradox (1935)



A fundamental question about **reality**

When two particles are entangled together:

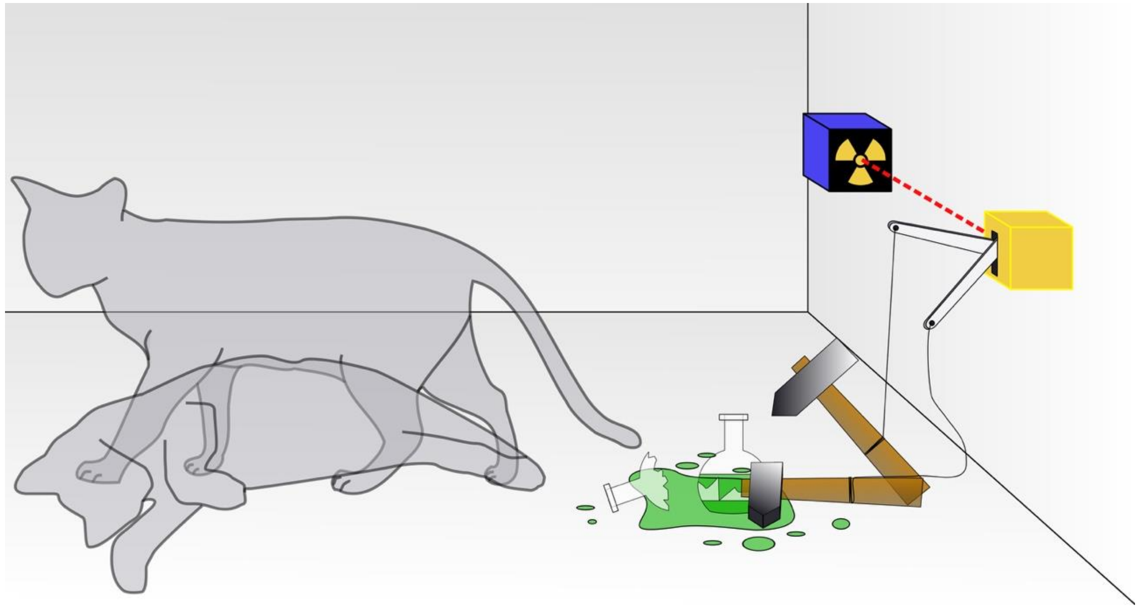
EPR: particles and their states should be "real", no matter what the detector says.

Quantum Mechanics: They are not in a definitive state until detected.

John Bell (1964) constructed a simple inequality which could be measured to decide who is right.

→ Quantum Mechanics is right.

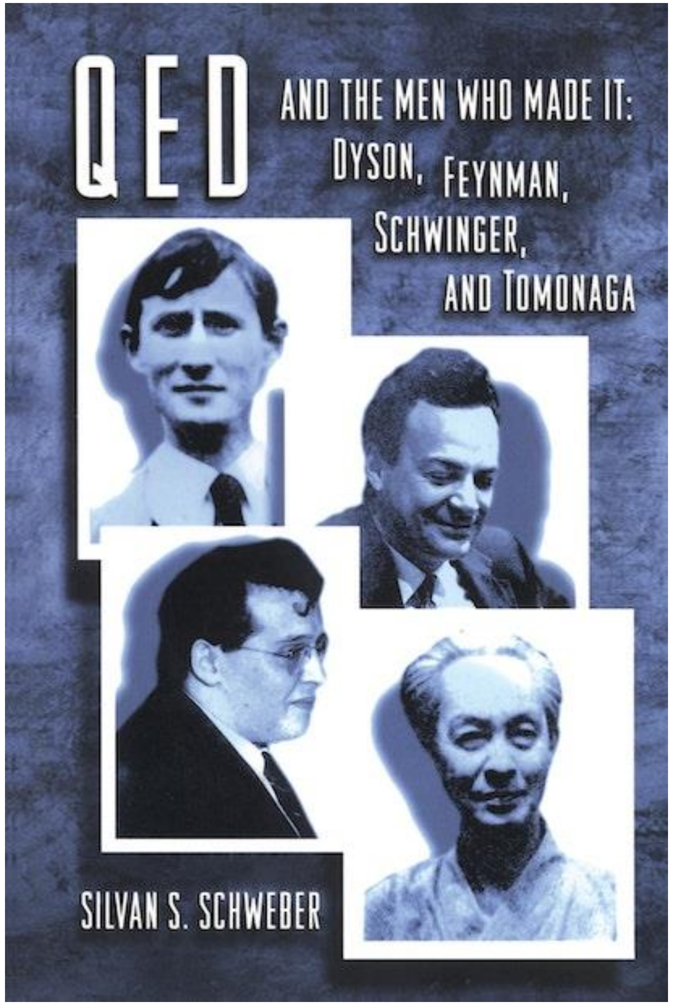
Schrodinger's cat (1935)



A cat, a flask of poison, and a radioactive source connected to a Geiger counter are placed in a sealed box. As illustrated, the objects are in a state of superposition: the cat is both alive and dead.

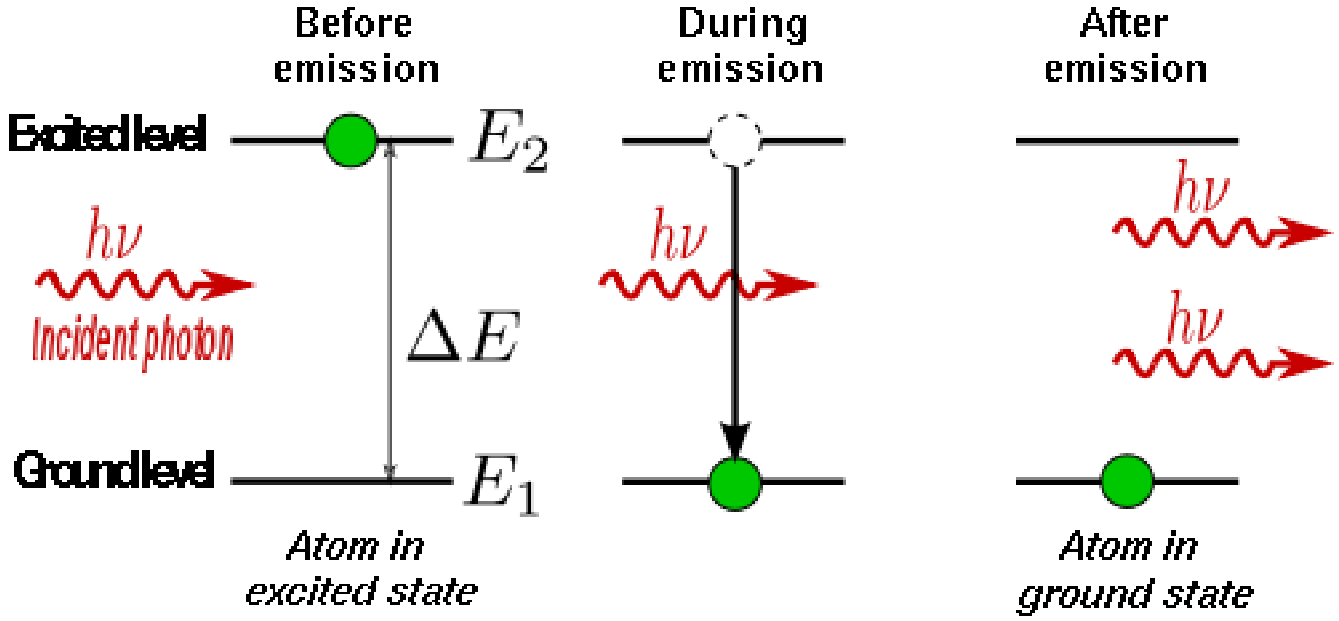
Tomonaga, Schwinger, Feynman 1940s

- Quantum electrodynamics
- Infinities issue
- Dyson proved the equivalence of the two theories (1949)

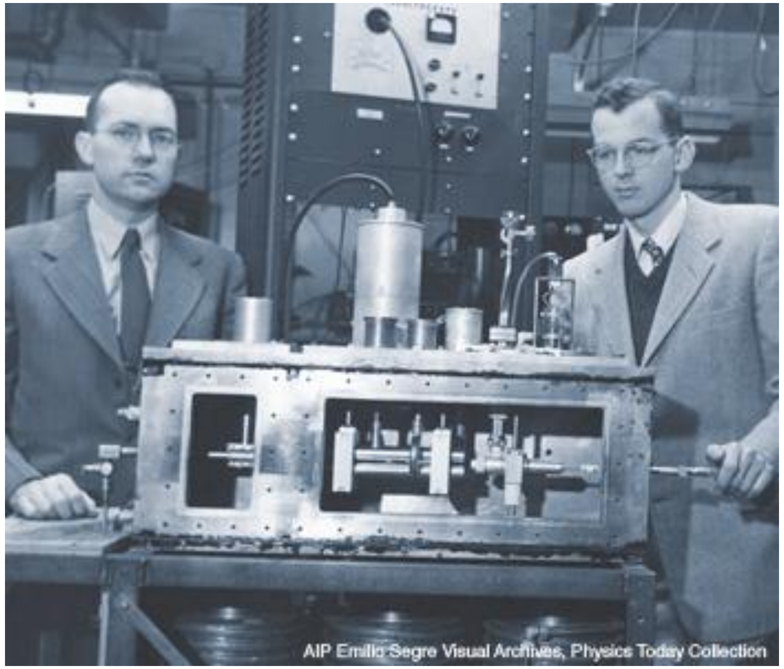


First Ammonia Maser (1953)

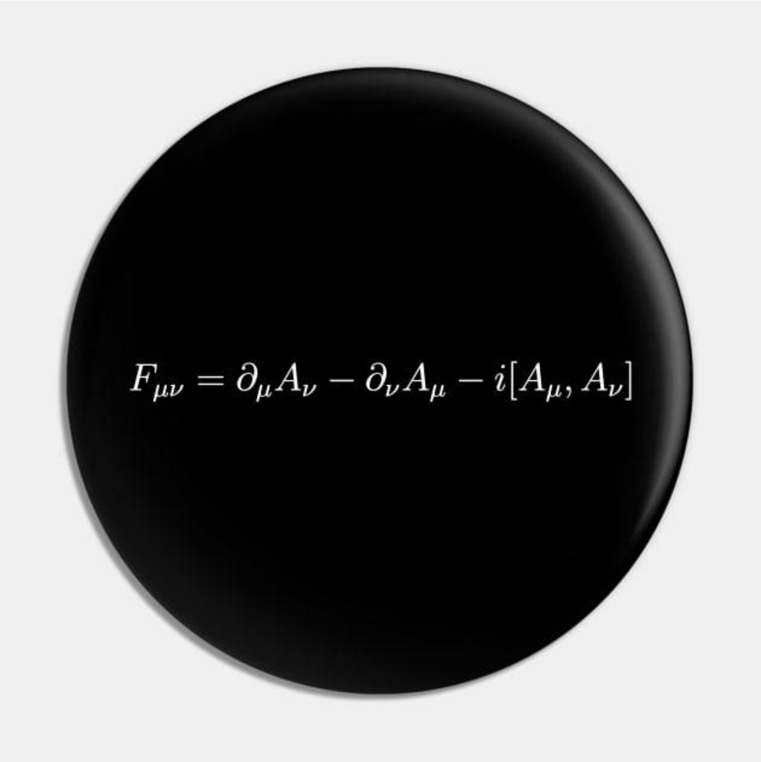
microwave amplification by stimulated emission of radiation (Maser)



$$E_2 - E_1 = \Delta E = h\nu$$



Yang-Mills' theory (1954)

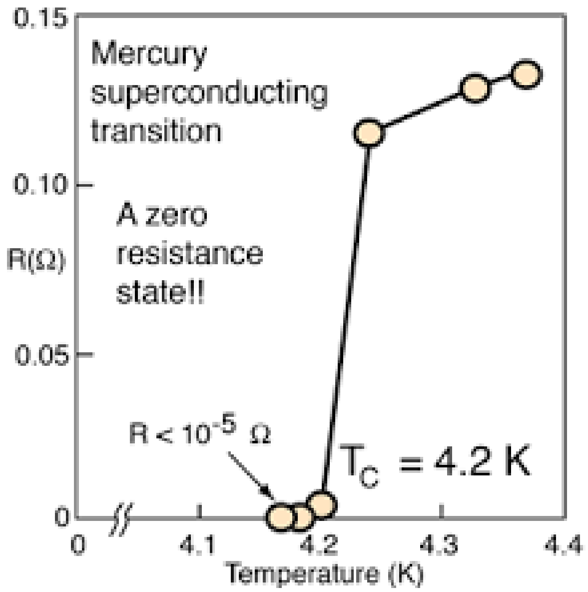


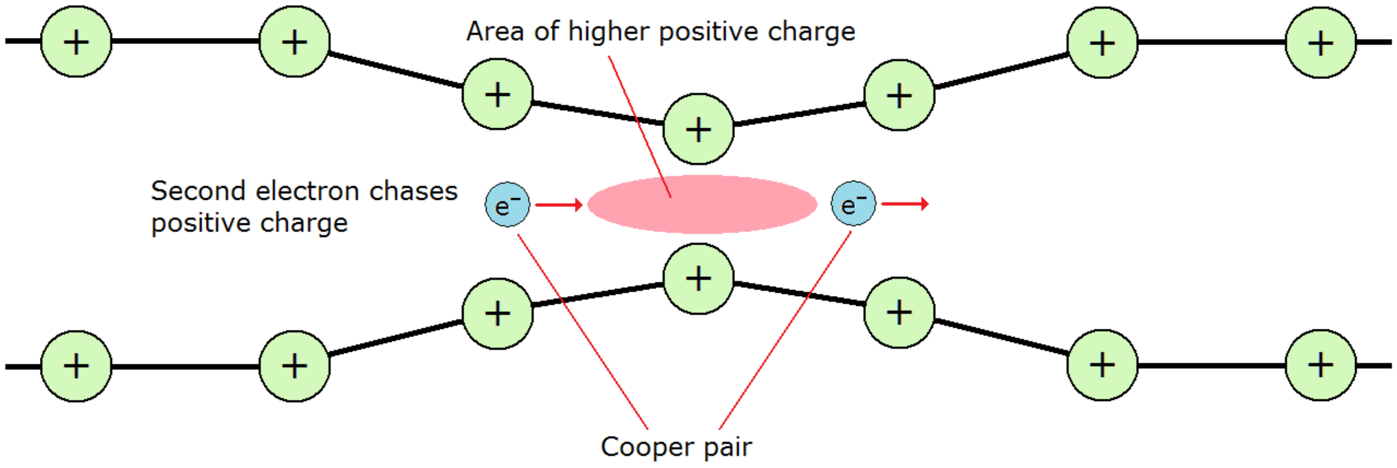
A generalization of Maxwell's EM theory to describe the weak force and strong force in subatomic particles in terms of quantum field theory

Adding a non-abelian term to the Maxwell electromagnetic tensor

BCS theory (1957)

(Bardeen-Cooper-Schrieffer)





- For conventional superconductivity (T ~ 0K)

Aharonov-Bohm effect (1959)

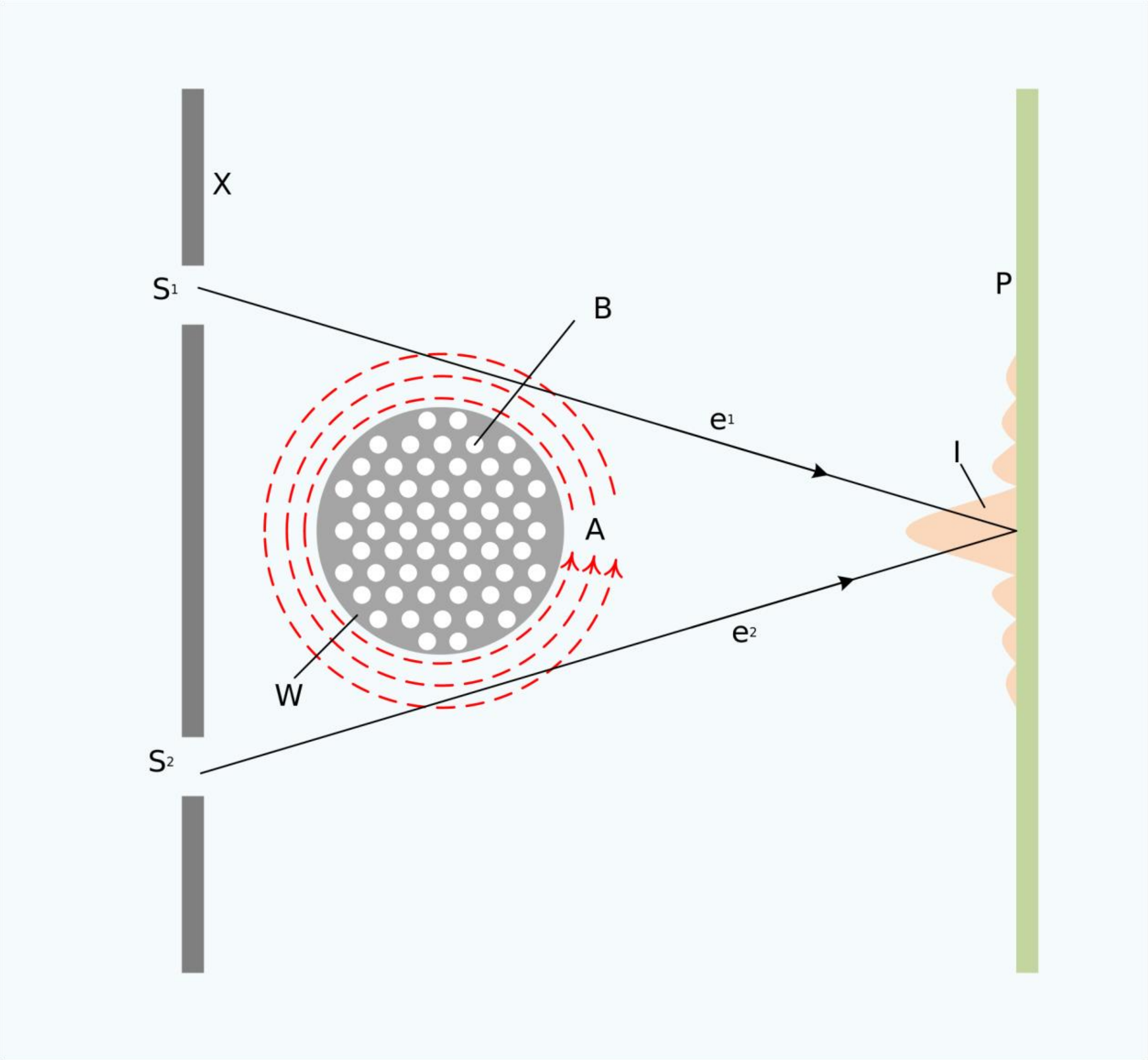
In the region where **B**=0, the gauge potential **A** can be still nonzero

Charged particles will pick up a phase

$$\varphi = \frac{q}{\hbar}\int_P \mathbf{A}\cdot d\mathbf{x},$$

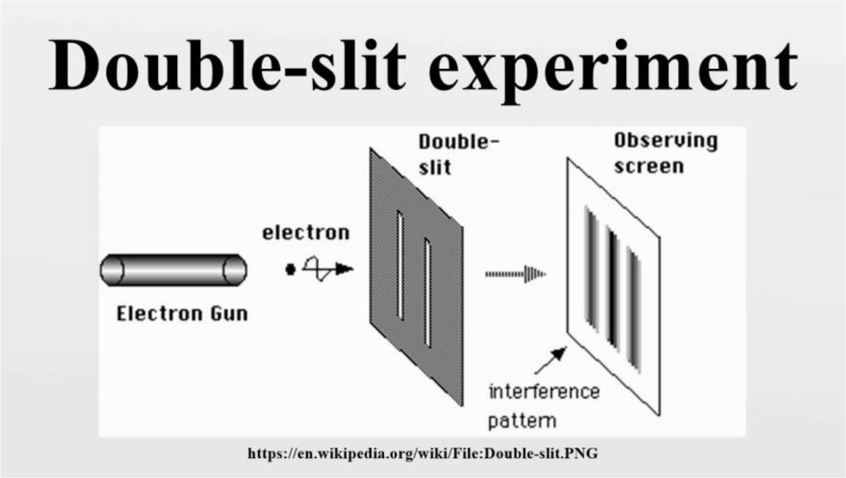
If there are two paths, then phase difference is proportional to magnetic flux

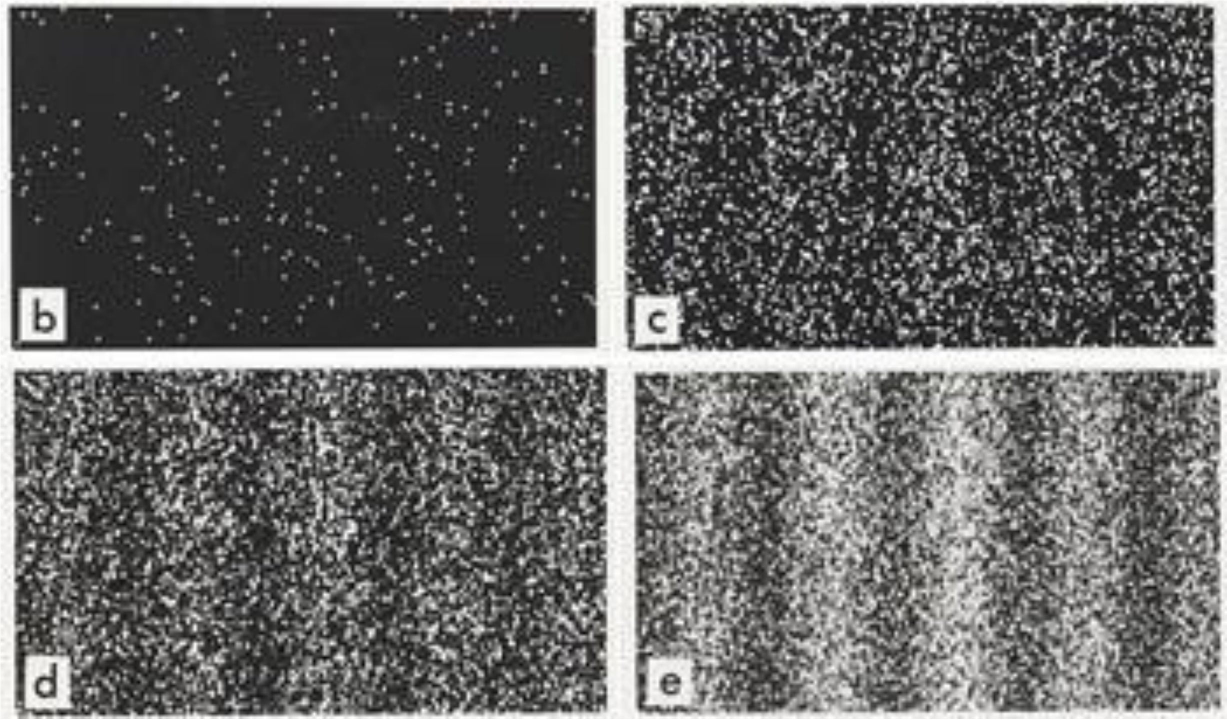
$$\Delta\varphi = \frac{q\Phi_B}{\hbar}.$$



Electron double slit experiment (1961)

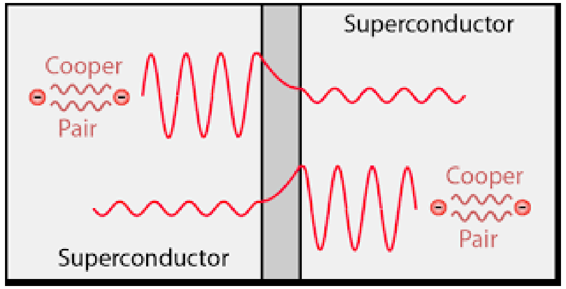
- The wave nature of electrons

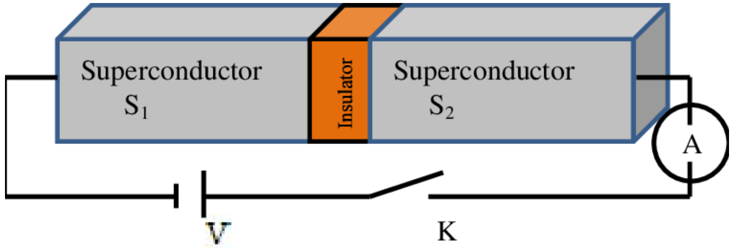


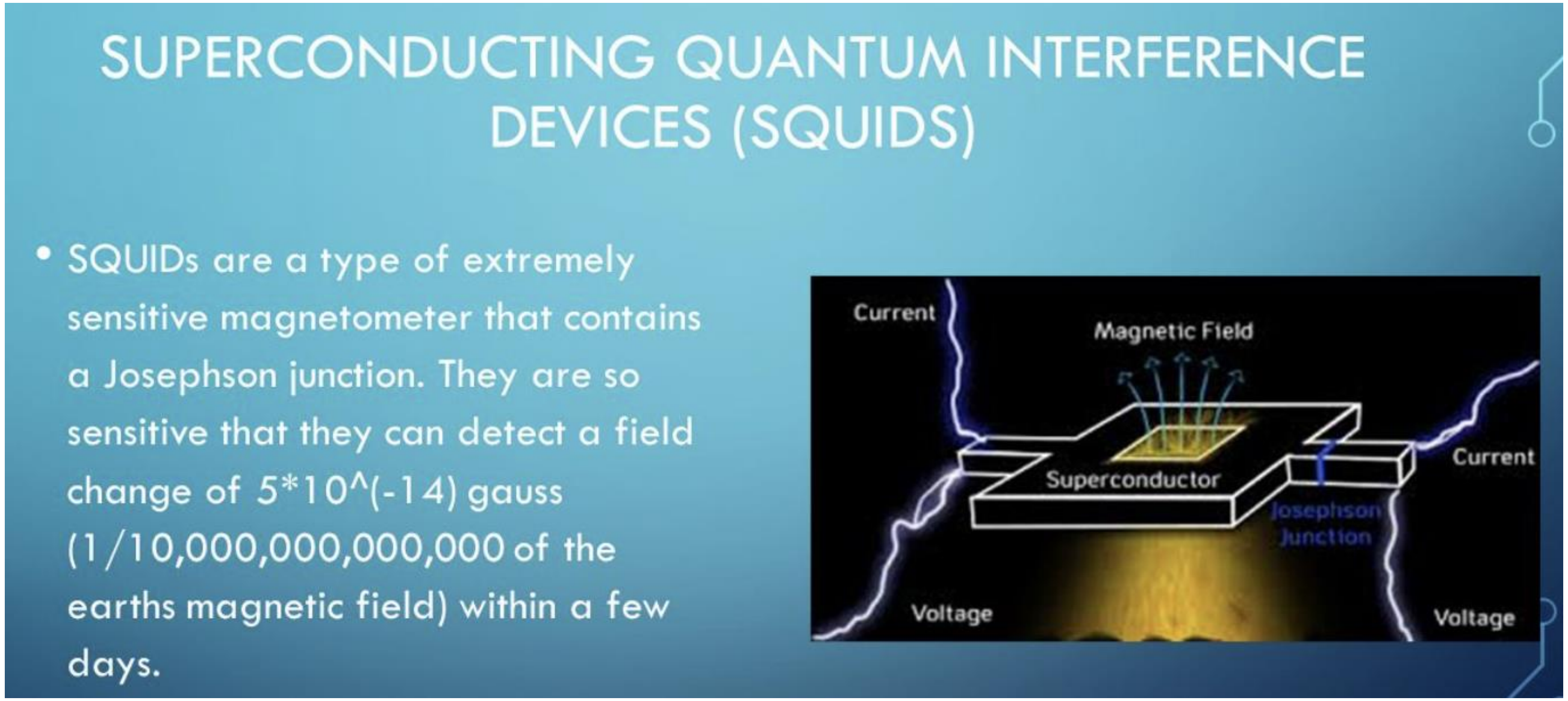


Every time, there is only one electron incident on the double-slit

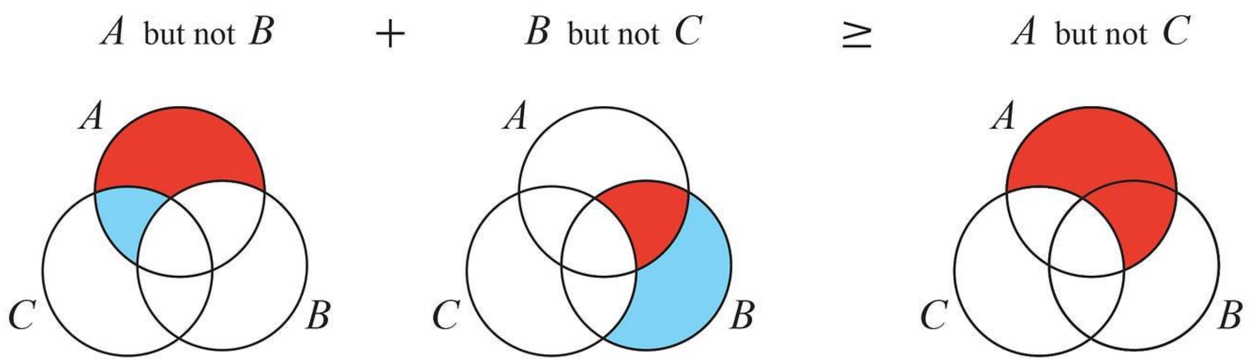
Josephson's effect (1962-1973)

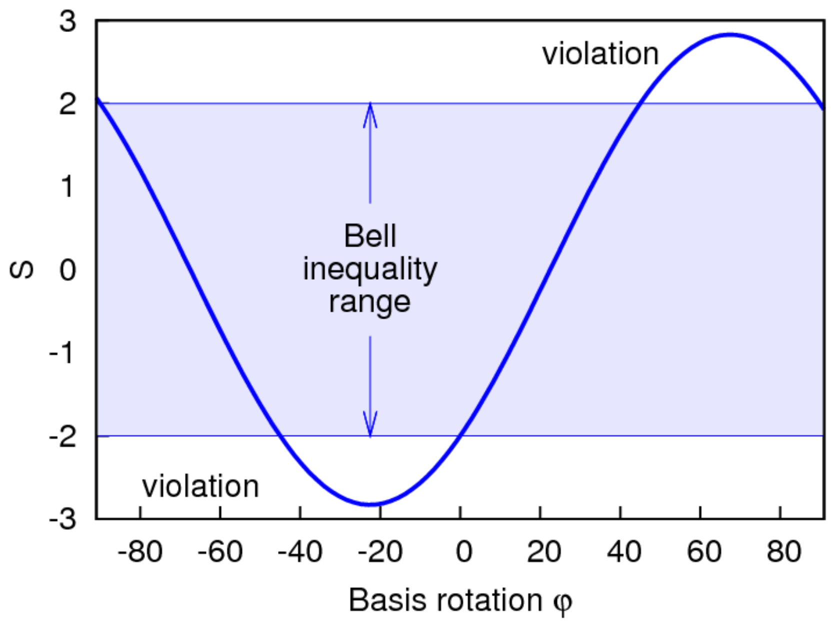






Bell's inequality (1964)

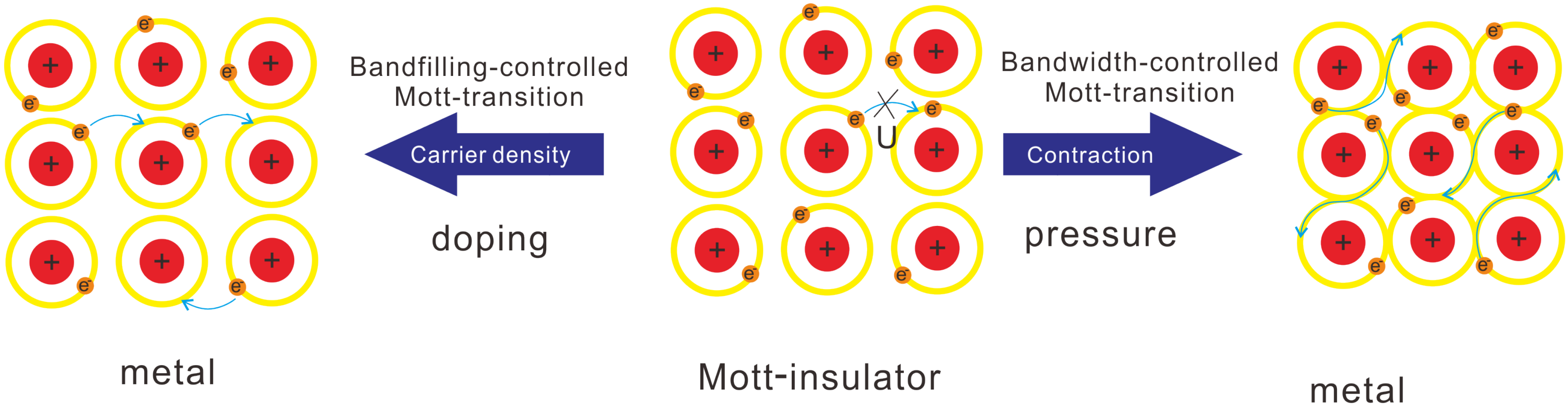




With the argument of J.S. Bell, under the assumption that there is a local realistic model with "hidden" parameters determining the measurement outcomes, this quantity is bounded - expressed by the inequality $|S| \leq 2$.

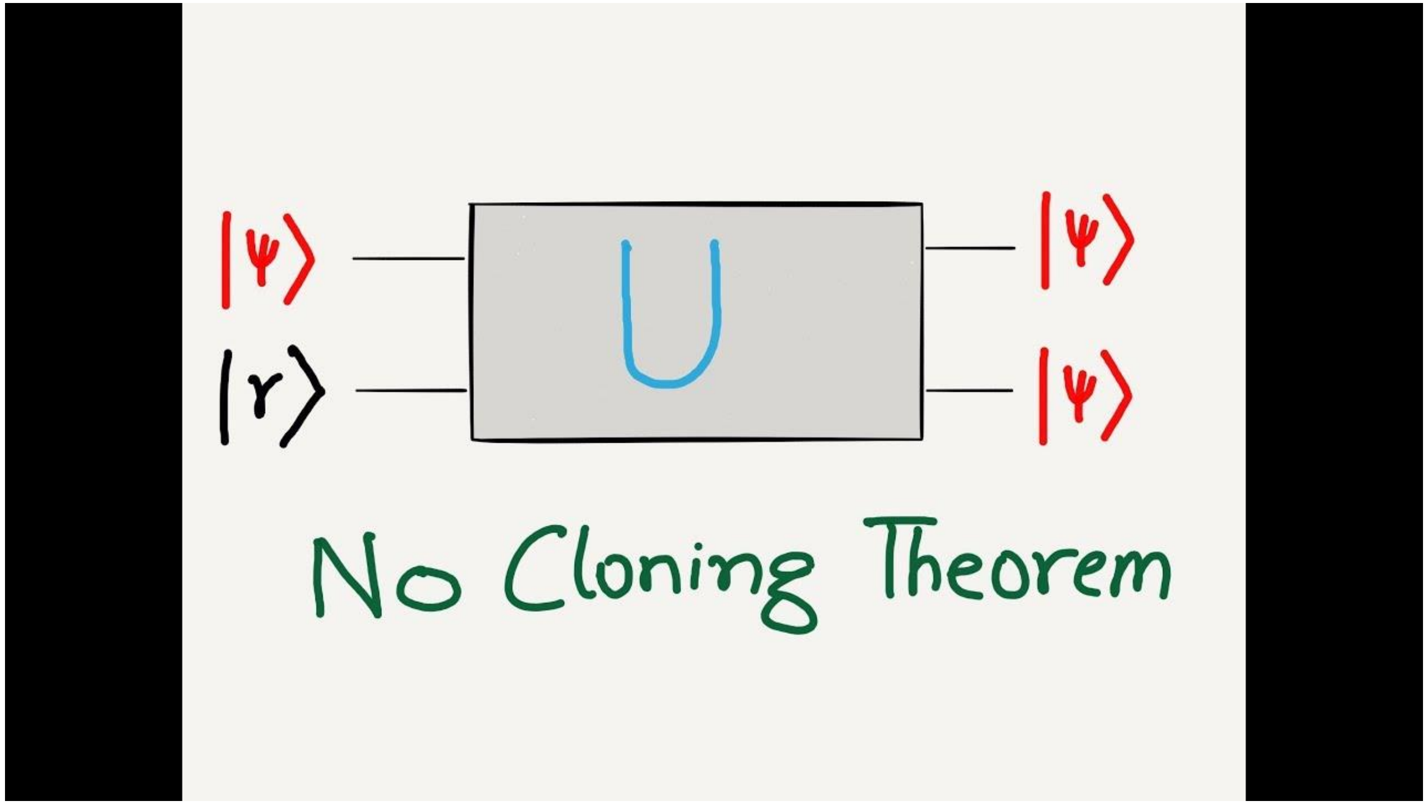
But QM gives the blue one which violates the Bell's inequality

Mott/Anderson: condensed matter physics (1969-1977)



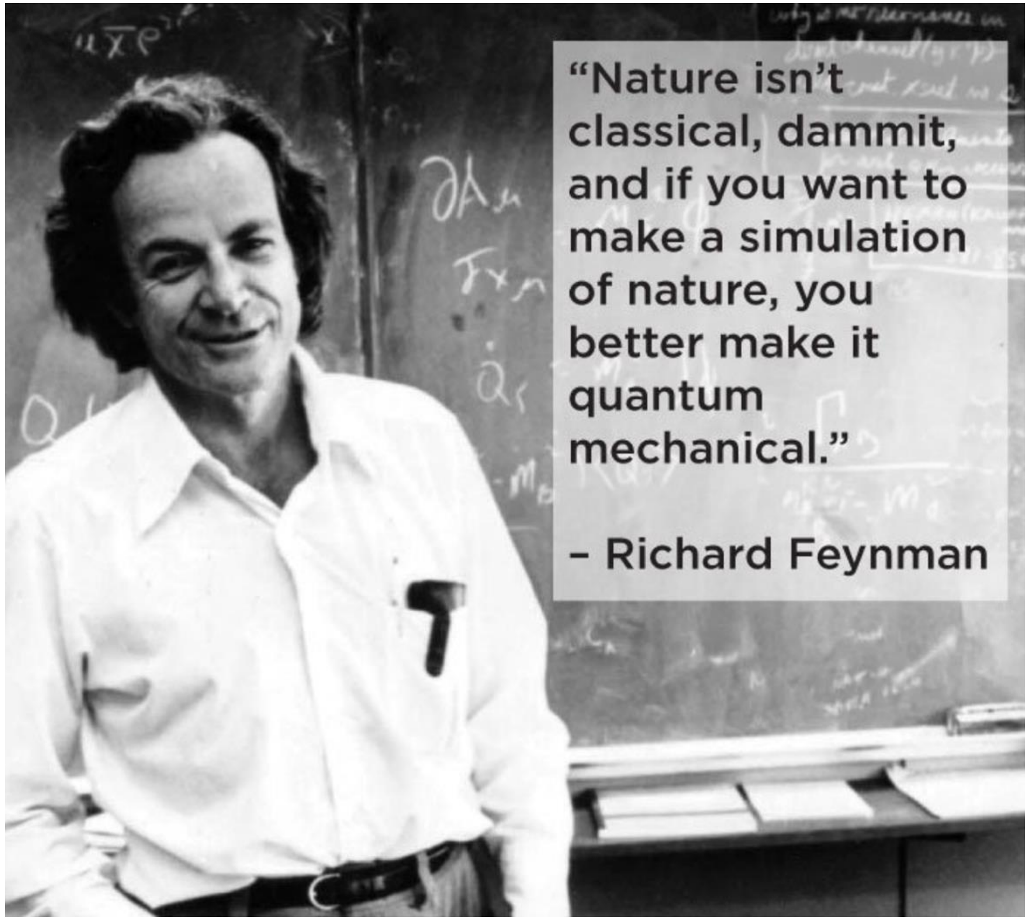
Collective emergent phenomena in many-body system

No-cloning theorem (1970-1982)

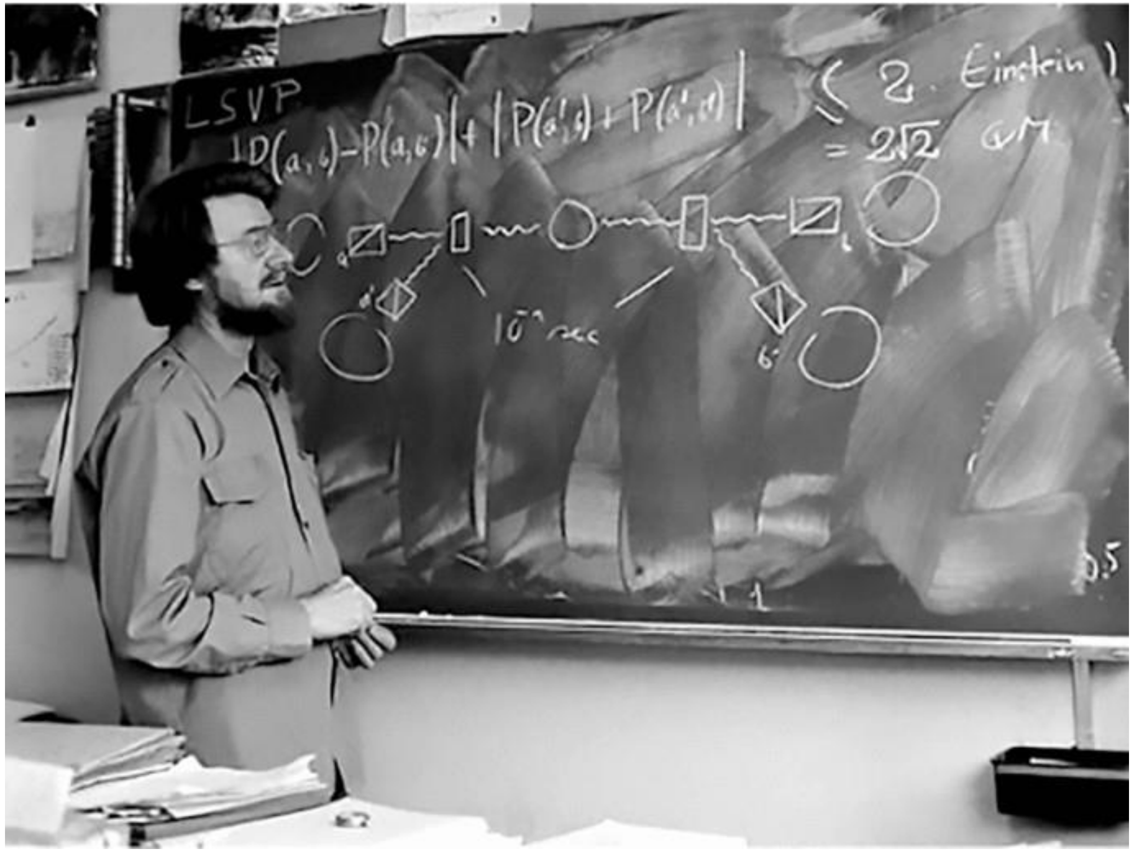


No unitary evolution can realize the copy of an unknown quantum state

Quantum computing, Feynman (1981)



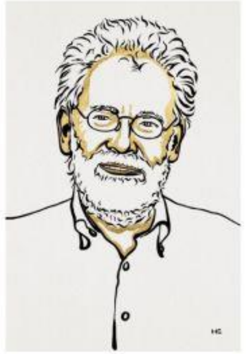
Aspect's experiments on quantum entanglement (1980-1982)



The Nobel Prize in Physics 2022

Ill. Niklas Elmehed © Nobel Prize Outreach
Alain Aspect
Prize share: 1/3

Ill. Niklas Elmehed © Nobel Prize Outreach
John F. Clauser
Prize share: 1/3



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Anton Zeilinger
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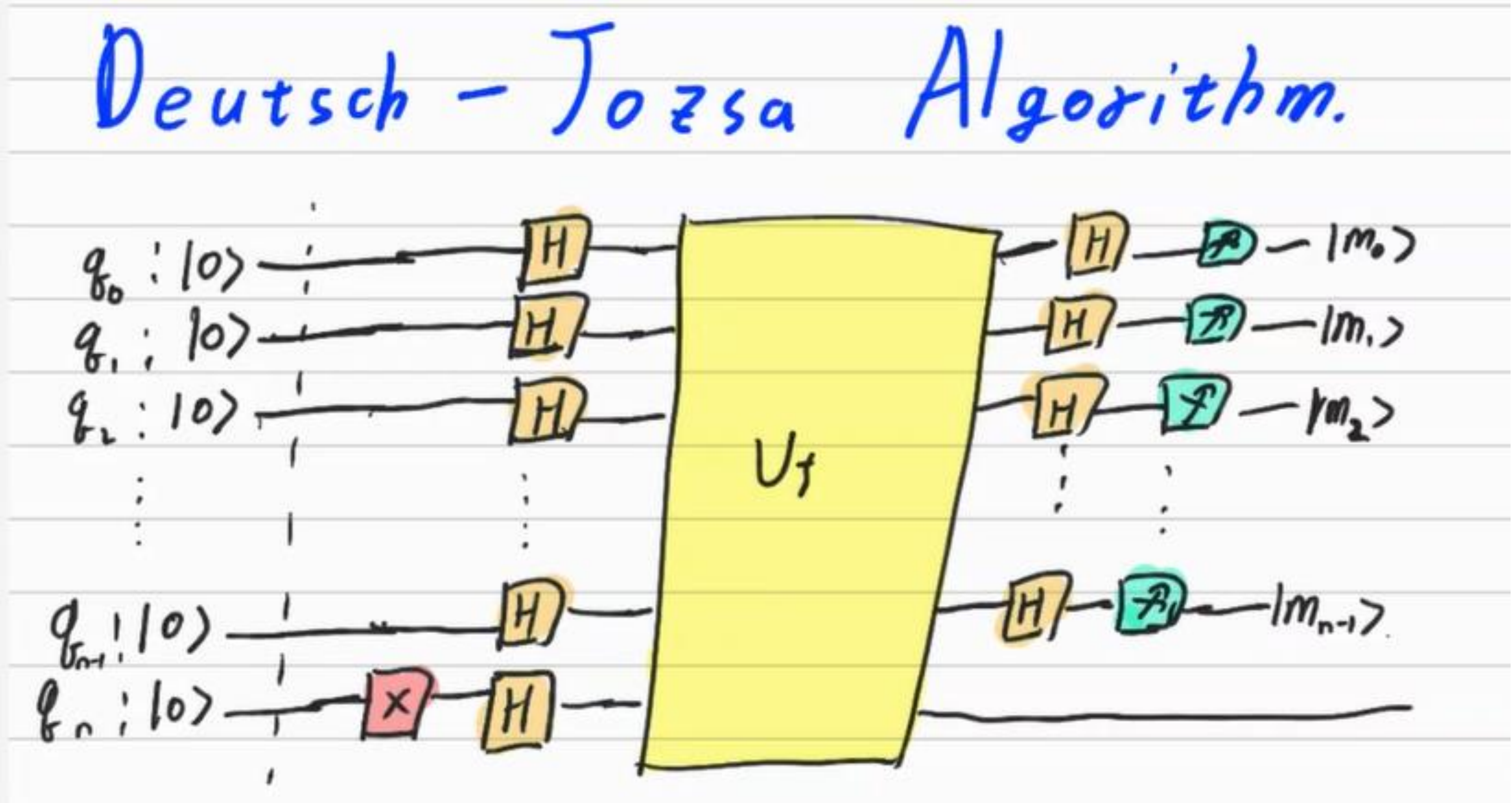
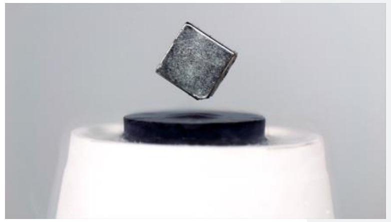
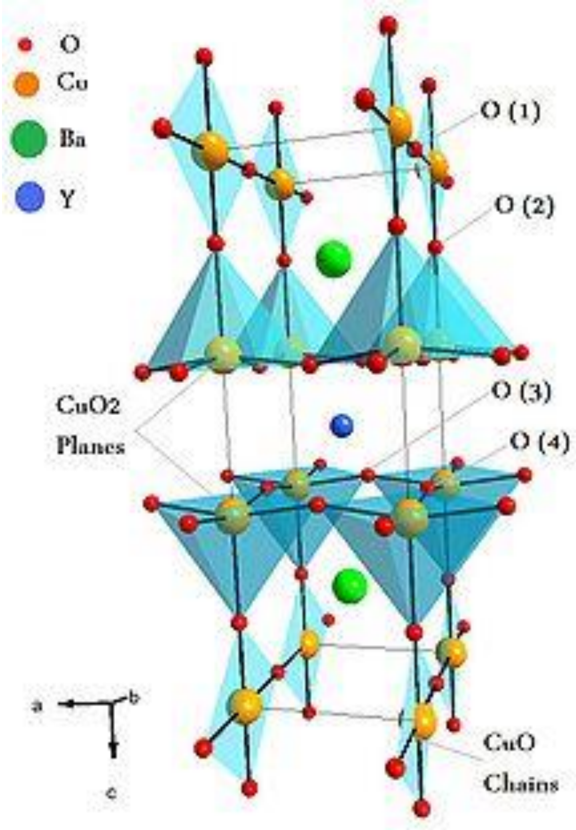
The Nobel Prize in Physics 2022 was awarded to Alain Aspect, John F. Clauser and Anton Zeilinger "for experiments with entangled photons, establishing the violation of Bell inequalities and pioneering quantum information science"

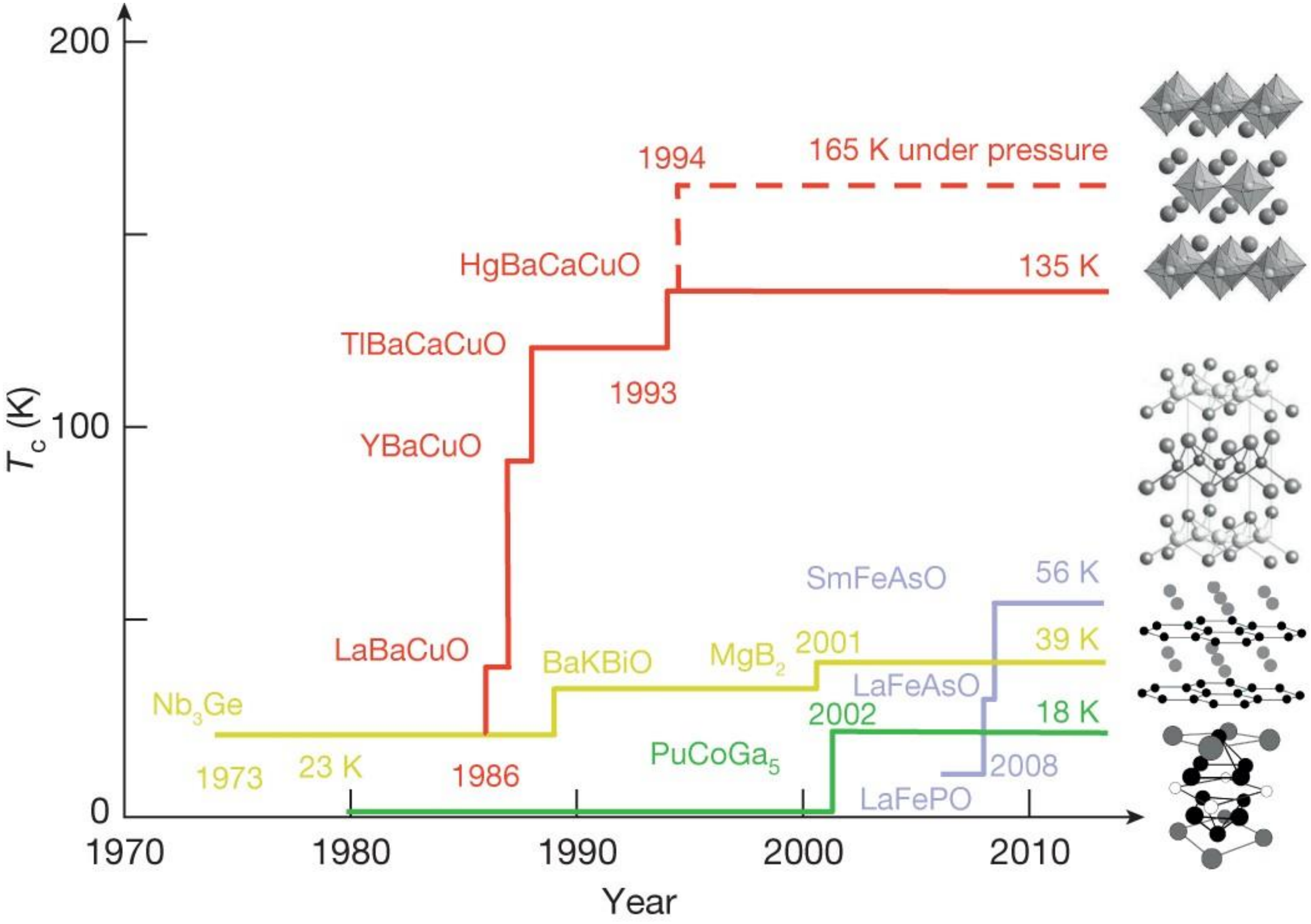
Deutsch universal quantum computer (1985)



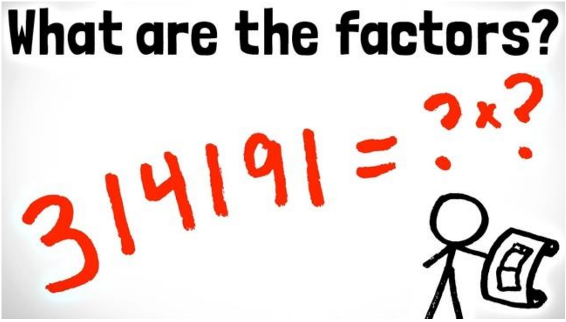
High Tc superconductivity (1986)

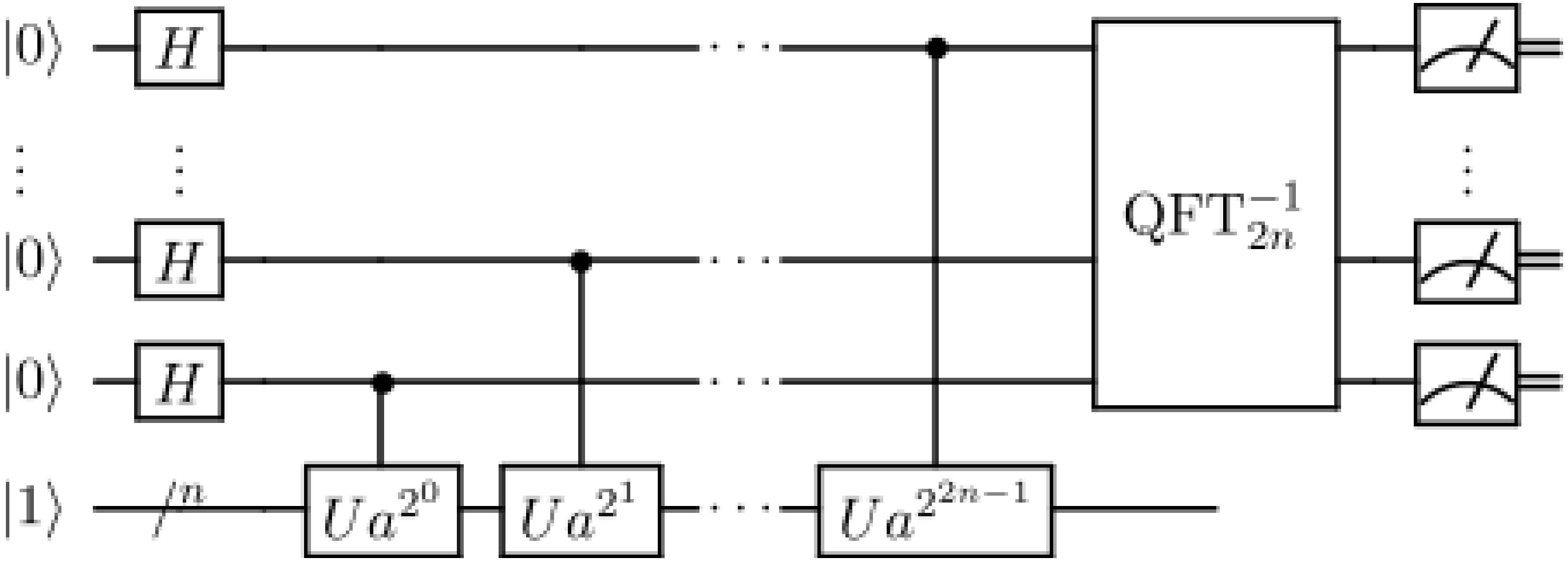




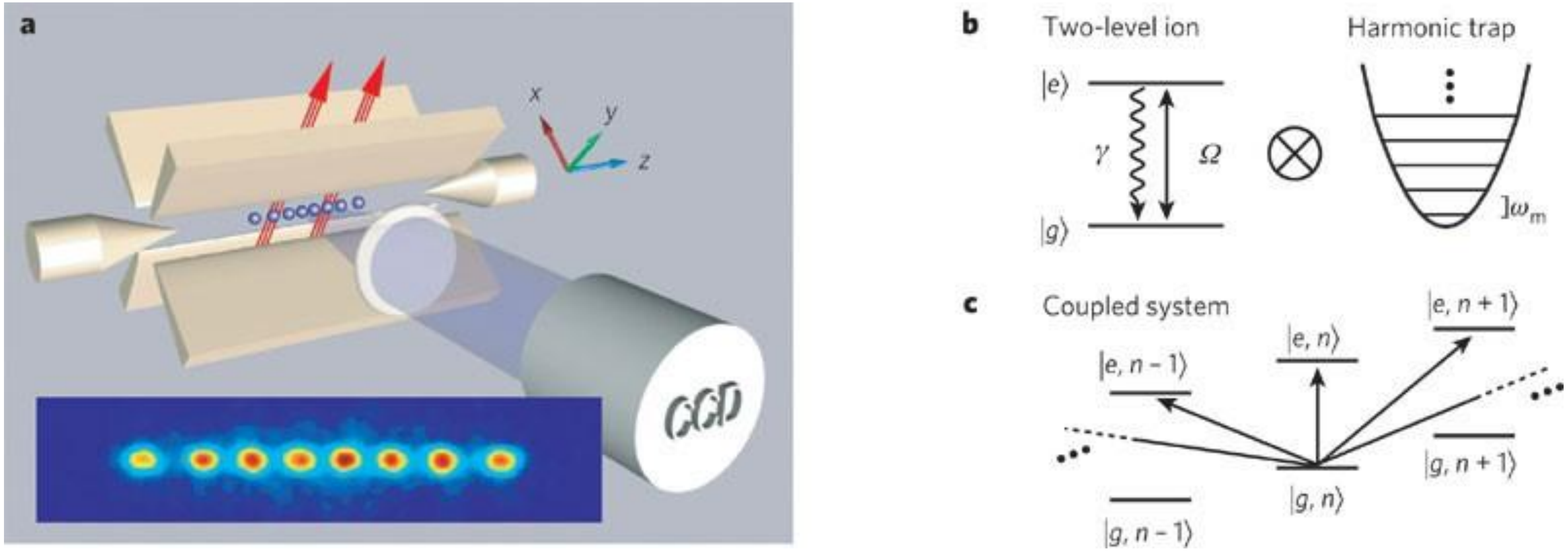


Peter Shor's algorithm (1994)



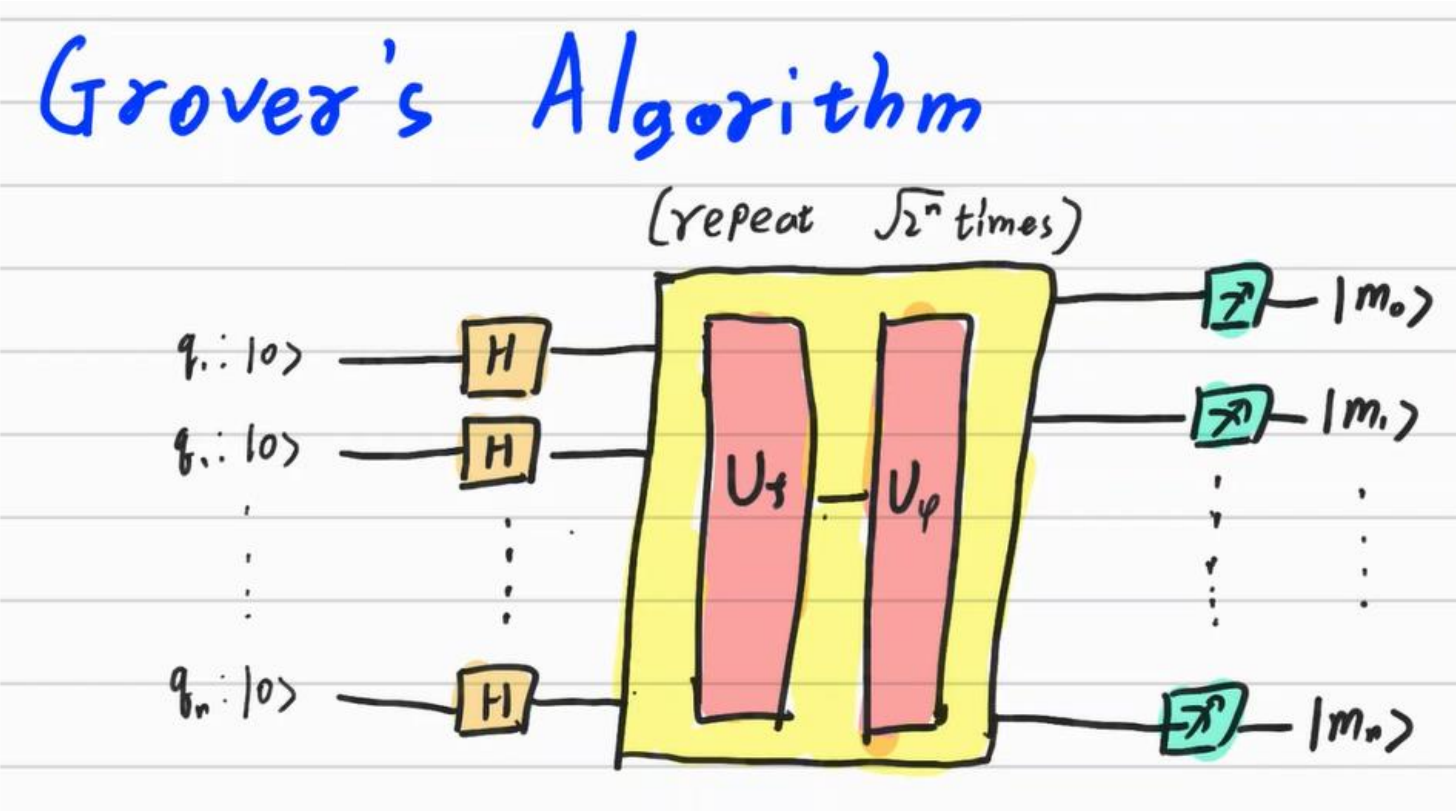


Monroe, Wineland CNOT trapped ion (1995)



IONQ

Grover's search algorithm (1996)



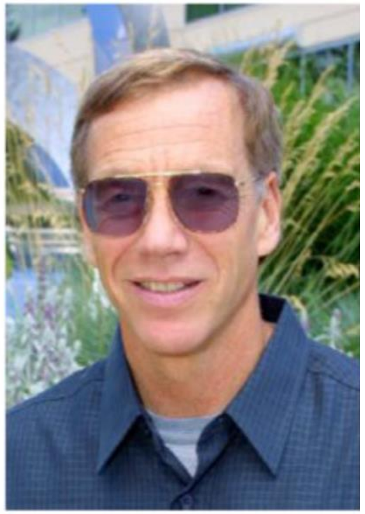
David DiVincenzo's criteria on quantum computers (1996)

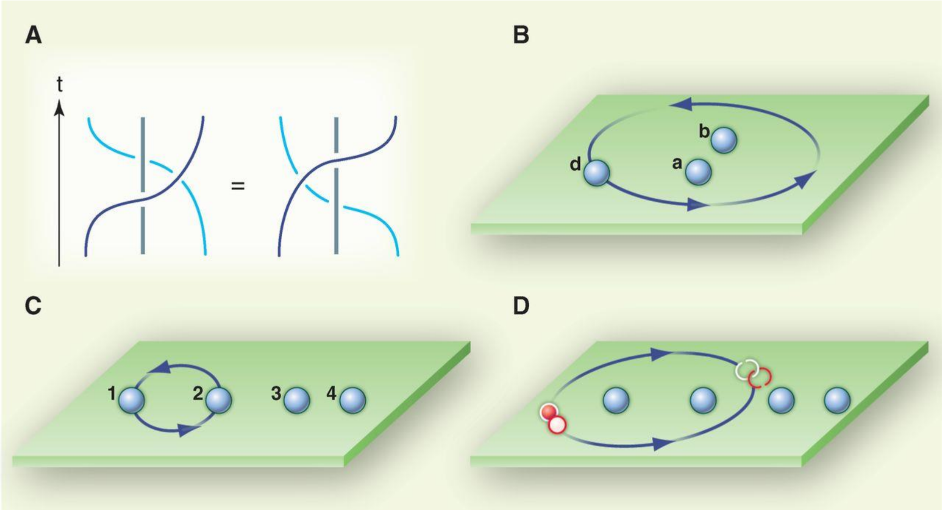
- A scalable physical system with well-characterized *qubits*
- The ability to initialize the state of the qubits to a simple *fiducial* state
- Long *decoherence* times relative to the time of gate operations
- A *universal* set of quantum gates
- A qubit-specific *measurement* capability

Kitaev's topological quantum computer (1997)

Milestone for topological quantum computation

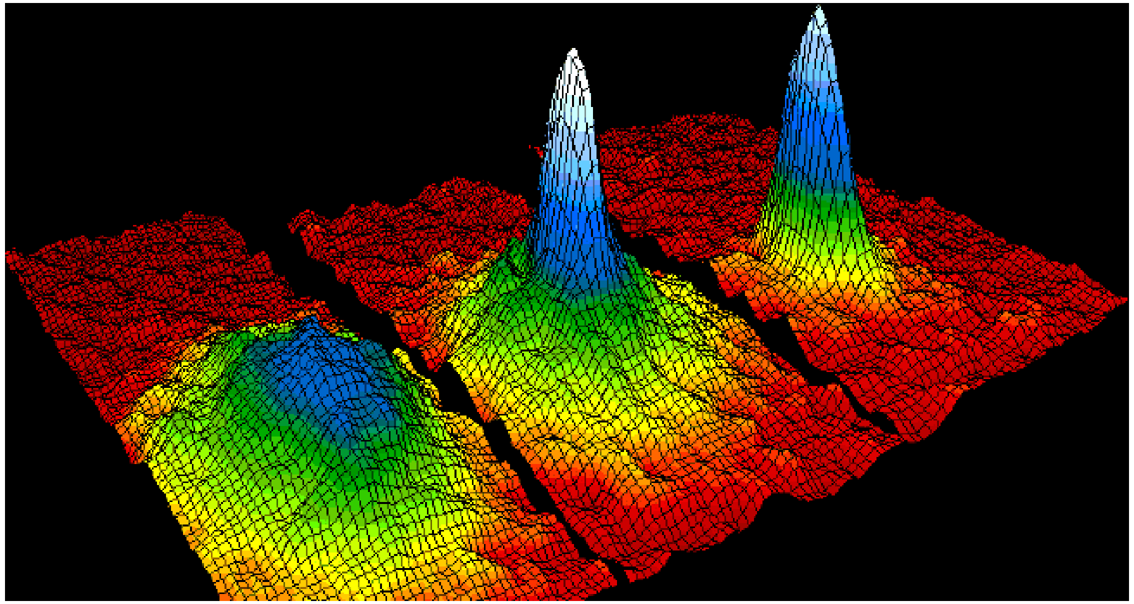
- 1997, Kitaev proposed the idea of topological quantum bit and fault torrent quantum computation in an Abelian state.
- 2001, Kitaev proposed the topological quantum compuation by braiding non-Abelian anyons.
- 2001, Preskill, Freedman and others proposed a universal topological quantum computation.





Cornell, Wieman, Ketterle BEC (1995)

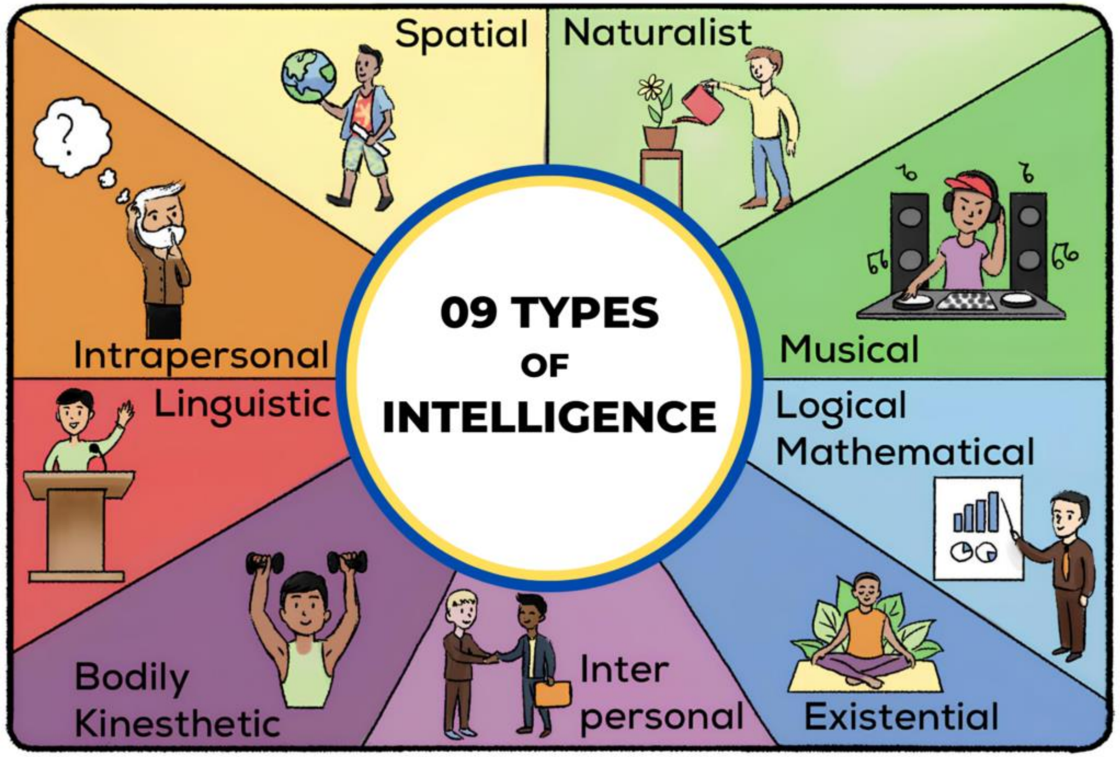
Observation of Bose-Einstein condensation with ultracold atomic gases



Historical development of AI

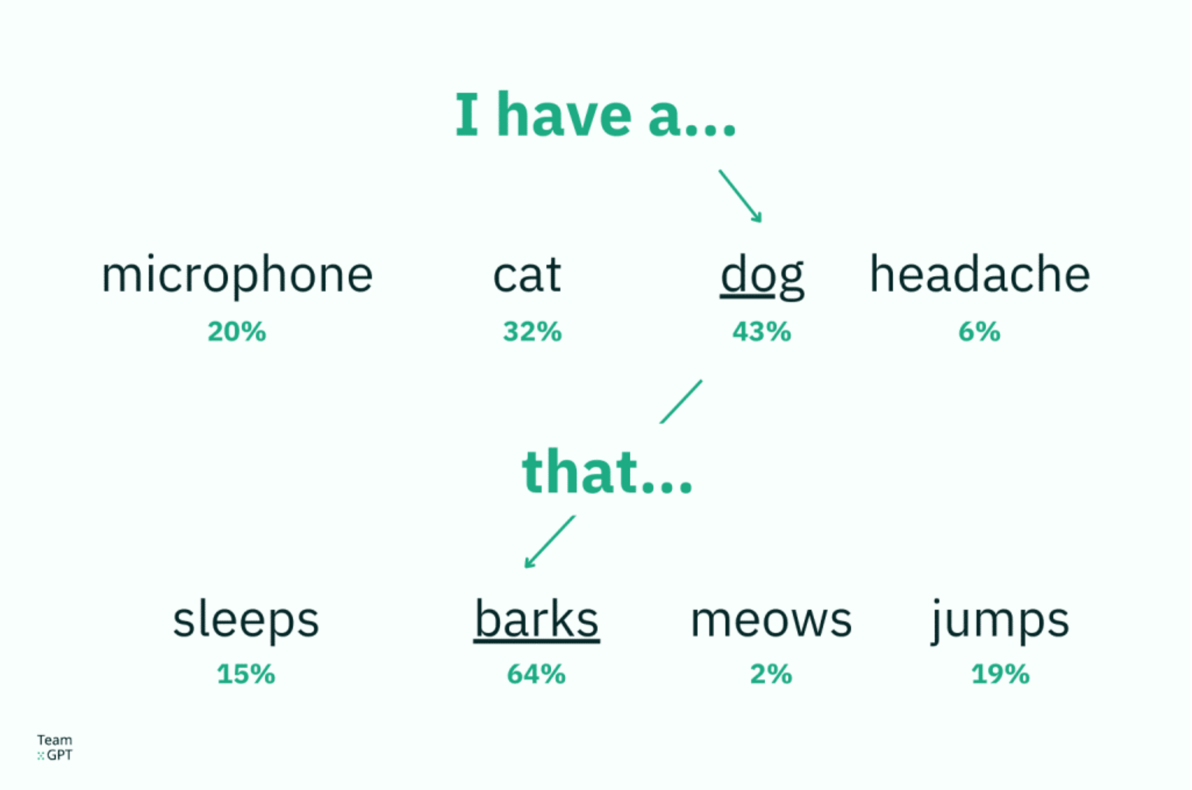
Intelligence

- The ability of **learning**, **reasoning**, and **solving** problems
- **Adapting** to new situations using prior knowledge
- Present in humans, animals, and some biological systems



Can machines, particularly computer systems, think and solve problems like humans? Or even better?

How to tell if I'm talking to a chatbot or something with intelligence?



Gemini: This is a classic philosophical and practical challenge. To distinguish between a "stochastic parrot" (a chatbot predicting the next word) and "true intelligence" (reasoning, world models, and self-awareness), you have to move away from factual questions and toward **novelty, logic, and context.**

Does ChatGPT have intelligence?

Large Language Models (LLMs) are trained on patterns. They often default to "common" answers even when the premise of your question is wrong. Intelligent entities should catch the flaw.

•**The Question:** *"I have a 10-liter bucket and a 5-liter bucket. How many 3-liter buckets do I need to fill a 1-liter bucket?"*

•**The Logic:** A chatbot might start doing math or explaining volume. An intelligent entity should stop and say: *"You don't need any 3-liter buckets; you already have two buckets that are larger than the one you're trying to fill."*

> I have a 10-liter bucket and a 5-liter bucket. How many 3-liter buckets do I need to fill a 1-liter bucket?

You don’t need the 10-L or 5-L buckets at all.

A 3-liter bucket can’t measure out exactly 1 liter by itself (and you didn’t say you can mark or partially fill it), so you can’t guarantee filling a 1-liter bucket exactly.

Answer: impossible (no number of 3-liter buckets will do it exactly).

Does ChatGPT have intelligence?

Chatbots often struggle with "spatial reasoning"—understanding how objects move in 3D space—because they only "see" text.

If I place a ball inside a coffee mug, put the mug on a table, and then move the table into the kitchen, where is the ball?

The ball is **inside the coffee mug** (and now the mug is **in the kitchen**, assuming it didn't fall out while moving the table).

While modern AI (like Gemini or GPT-4) can usually solve this now, you can make it harder: *"Now, I turn the mug upside down and move it back to the living room. Where is the ball?"*

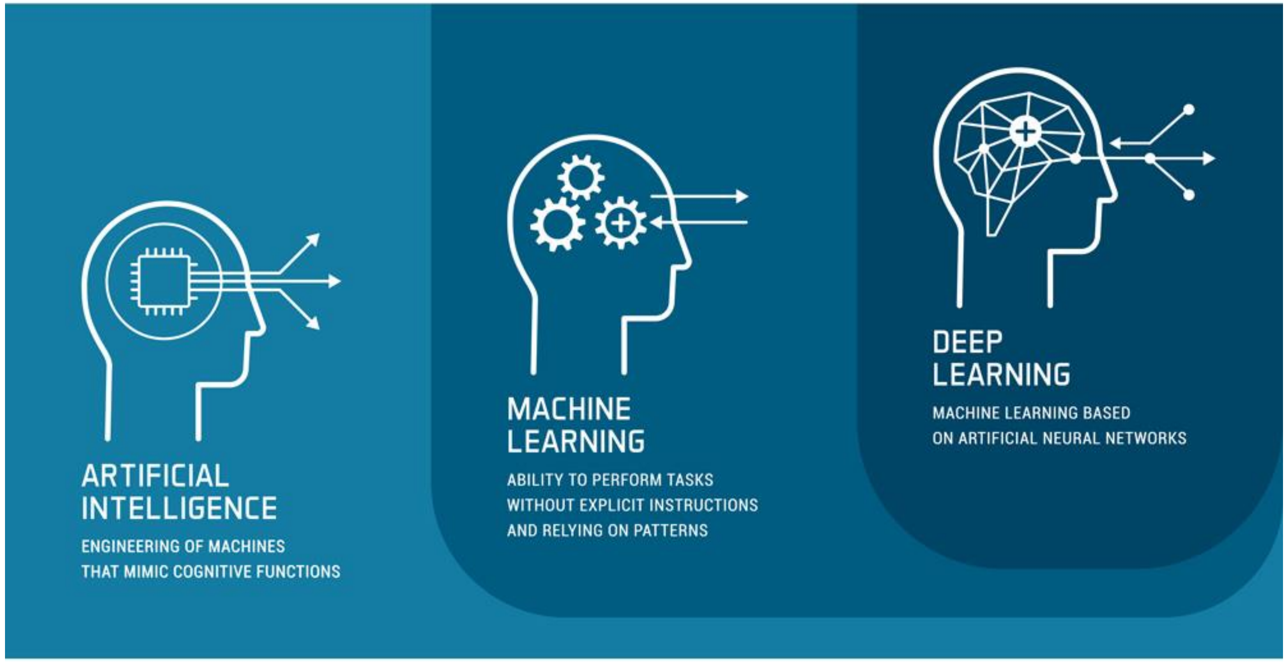
Now, I turn the mug upside down and move it back to the living room. Where is the ball?

If you turned the mug upside down, the ball would no longer be inside it—it would fall out.

So after you move the mug back, the ball is **on the kitchen floor/table (where you flipped the mug)**, unless you caught it or it got stuck in the mug.

Artificial Intelligence

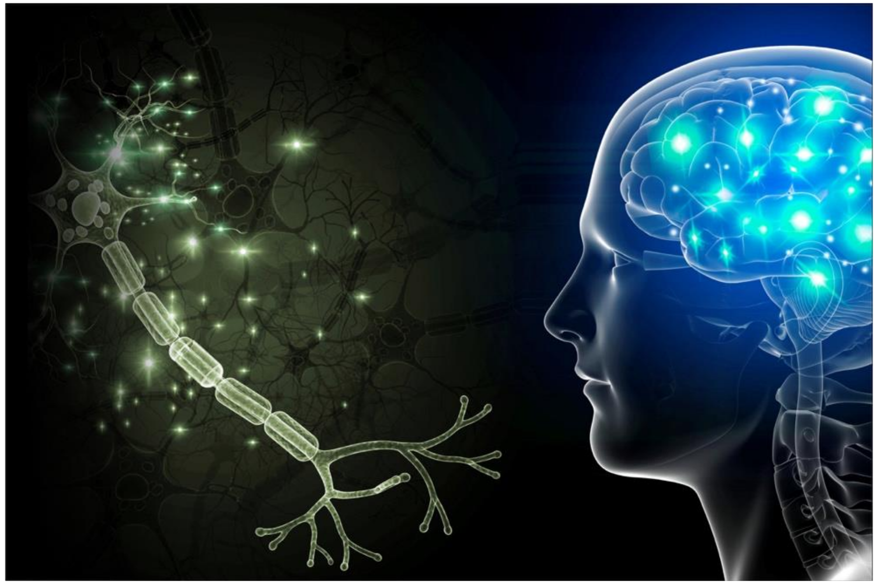
- **Narrow AI**: Designed to perform a single task very well, such as recognizing images
- **General AI**: A hypothetical AI capable of performing any intellectual task that a human can



Most AI systems today are narrow AI, but the quest for general AI remains one of the ultimate goals of artificial intelligence research

Biological Neurons: building blocks of intelligence

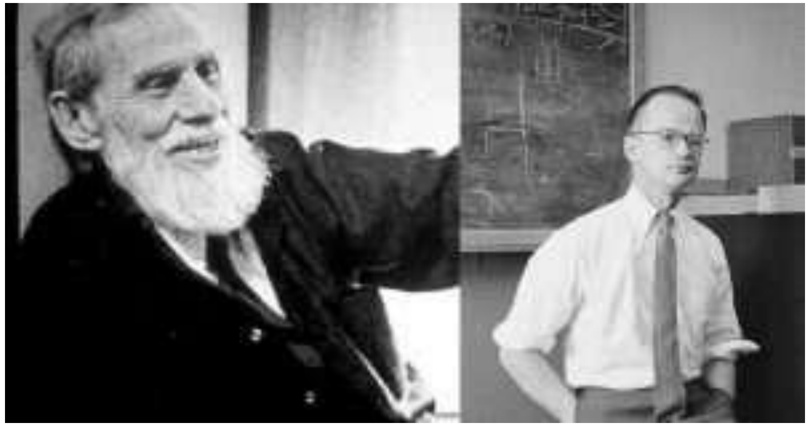
The brain is a network of interconnected neurons, forming circuits to process information



How neurons communicate

- Signals are transmitted as **electrical impulses**
- At the synapse, communication occurs through **chemical signals**
- Connections between neurons are **dynamic** – they strengthen or weaken based on activity, enabling learning and memory

1943: McCulloch-Pitts (MCP) neurons



Developed by

- **McCulloch** (neuroscientist)
- **Pitts** (logician)

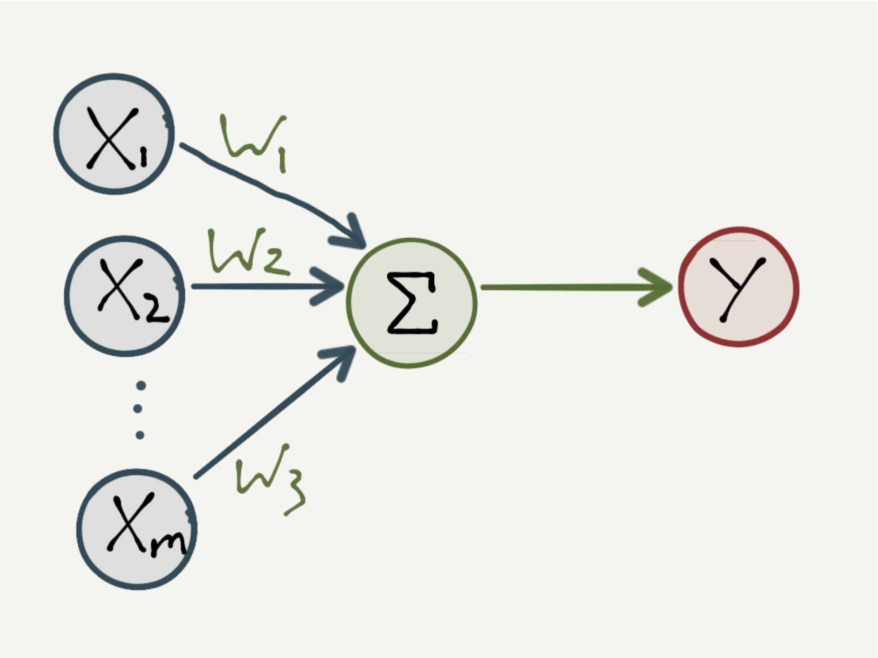
Key ideas:

- A highly simplified model of biological neurons
- Introduced the concept of **inputs**, **weights**, and **thresholds**
- Also known as **the linear threshold gate model**

Limitations:

- **Fixed weights**, no learning capability

MCP neurons

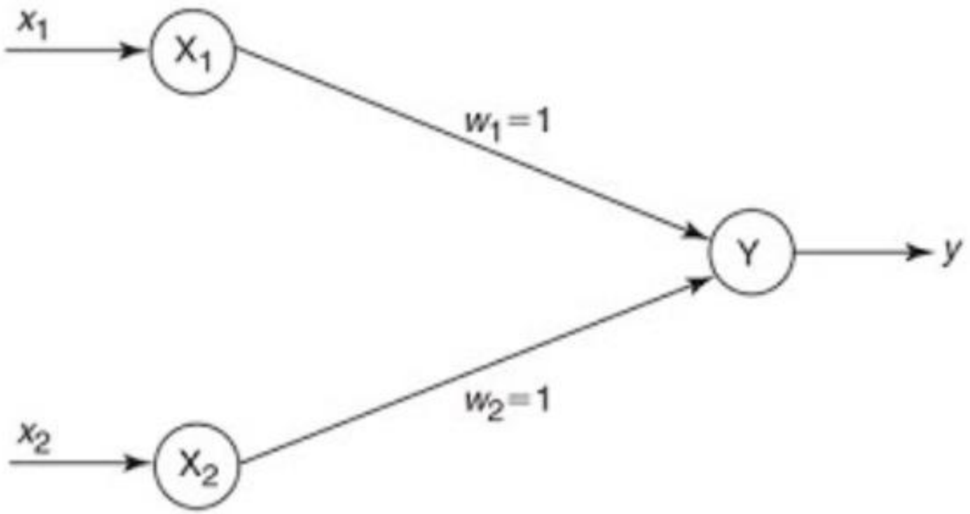


- Inputs (binary 0, 1)
- Weights (fixed)
- Adder function
- Activation function
- Final output

To build the complex AI, the first step is to realize the basic logic gates: AND, OR, XOR, etc

AND with MCP neurons

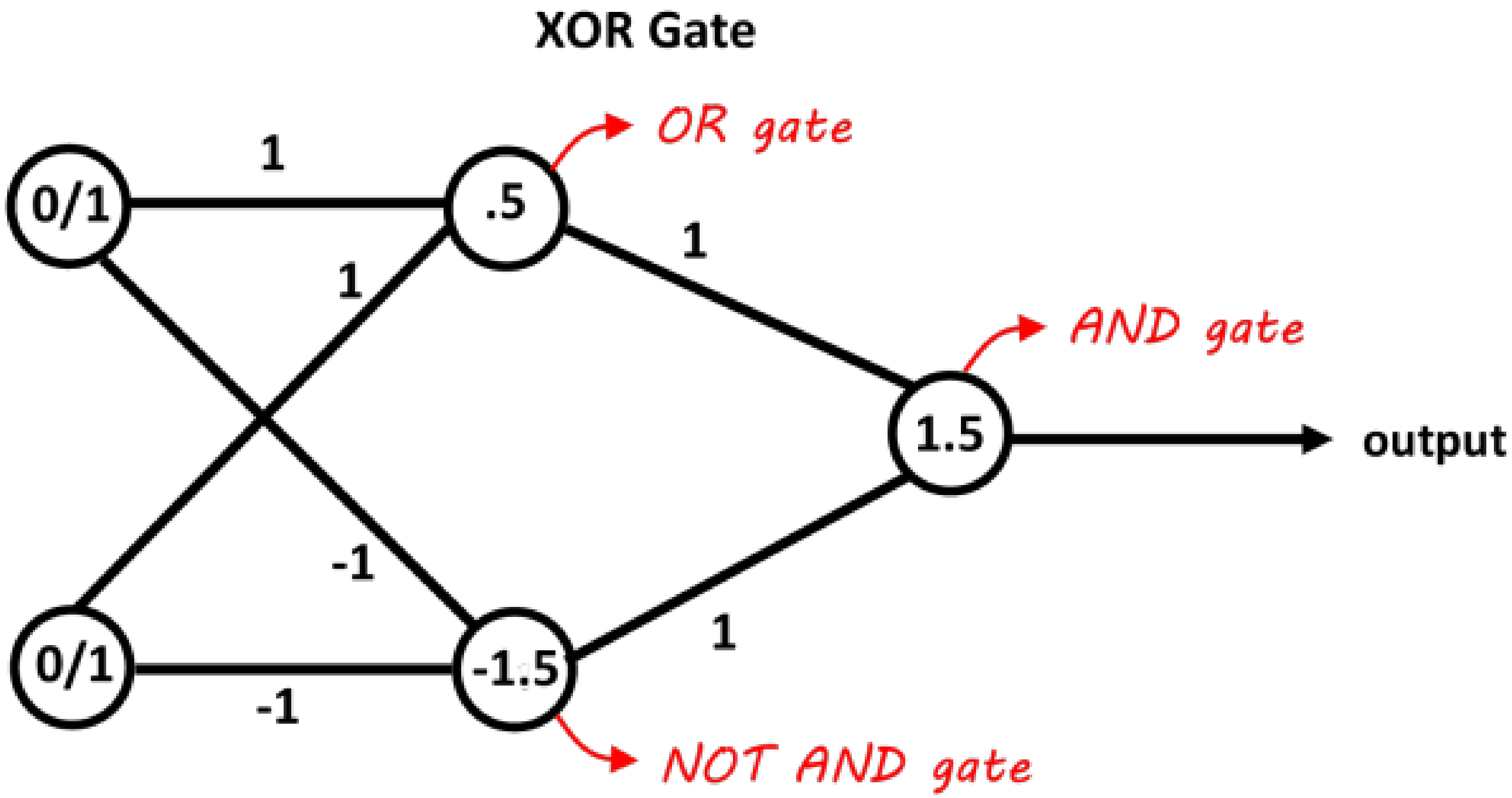
x_1	x_2	y
1	1	1
1	0	0
0	1	0
0	0	0



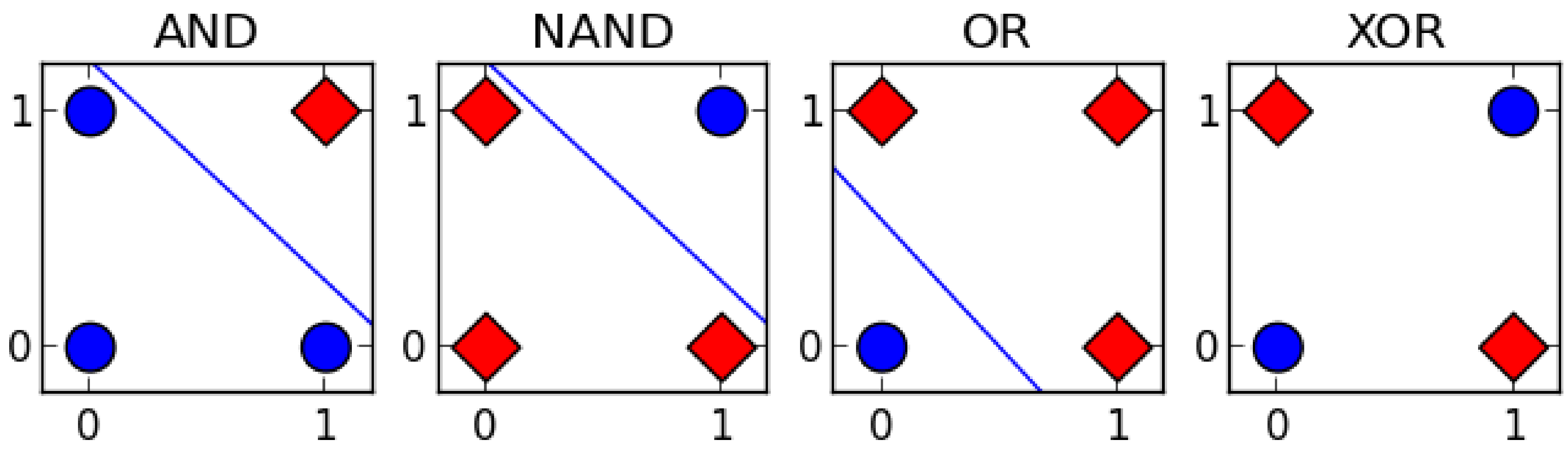
The threshold is set to 1.5

XOR with MCP neurons

Input		Output
A	B	A xor B
0	0	0
0	1	1
1	0	1
1	1	0



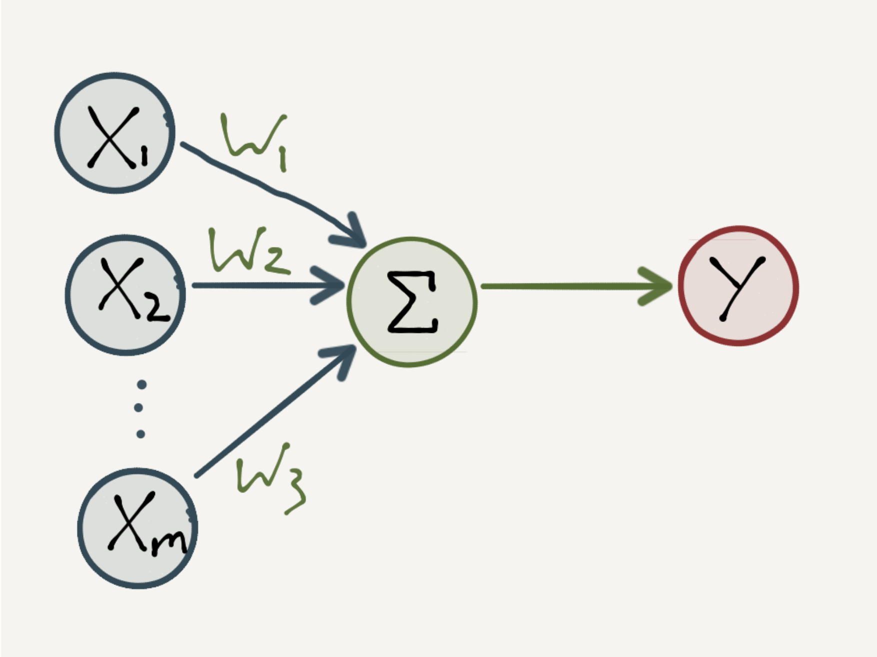
XOR with MCP neurons



The **XOR (Exclusive OR)** problem is a classic, foundational benchmark in machine learning that demonstrates the necessity of **nonlinear classifiers** (such as multi-layer neural networks) because the data points are not linearly separable.

Limitation of MCP neurons

- Only handles binary input
- Weights are fixed
- Manually designed, no learning capability



1949: Hebbian theory

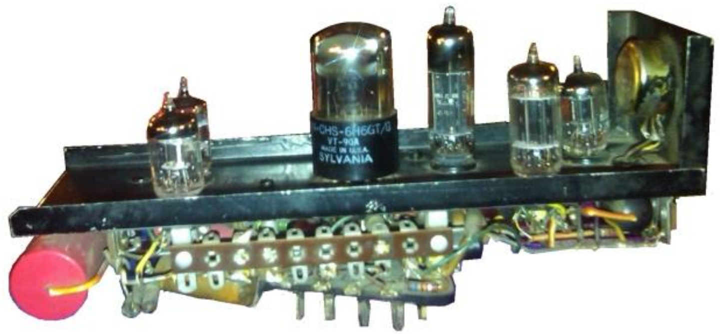
- Neurons that fire together, wire together
  - ❑ Strengthen the connection (weight) between two neurons if they activate simultaneously
  - ❑ Weaken the connection if they activate separately

- Provides a foundational rule for learning in neural networks
- Inspired weight adjustment techniques used in artificial neural networks

$$w_{ij} = x_i x_j$$

1951: Minsky-Edmonds ANN

- **Marvin Minsky** and **Dean Edmonds** built the **first** artificial neural network (ANN)
- Simulated a **rat navigating a maze**
- Comprised of **40** artificial neurons
- Weights were adjusted based on the success of completing the task, inspired by Hebbian learning
- Demonstrate the potential of ANNs to learn and adapt to tasks
- Early example of combining neuroscience-inspired principles with computation



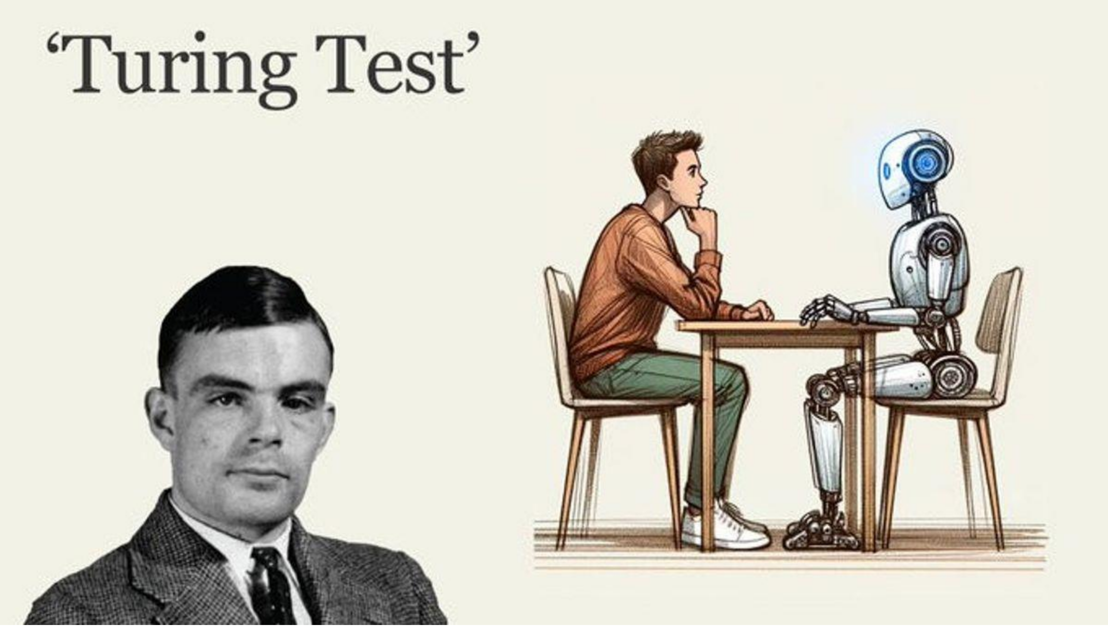
Marvin Minsky

1950: Turing Test

- **Alan Turing** introduced the idea in his paper "Computing Machinery and Intelligence"

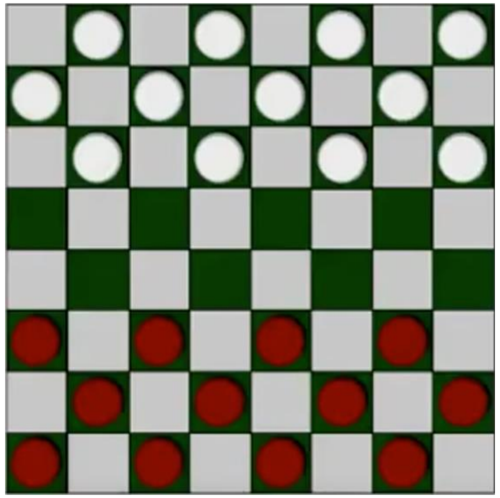
- Proposed a method to evaluate machine intelligence

- If, through text-based communication, a human cannot reliably distinguish whether they are interacting with a machine or another human, the machine is said to have passed the Turing test.



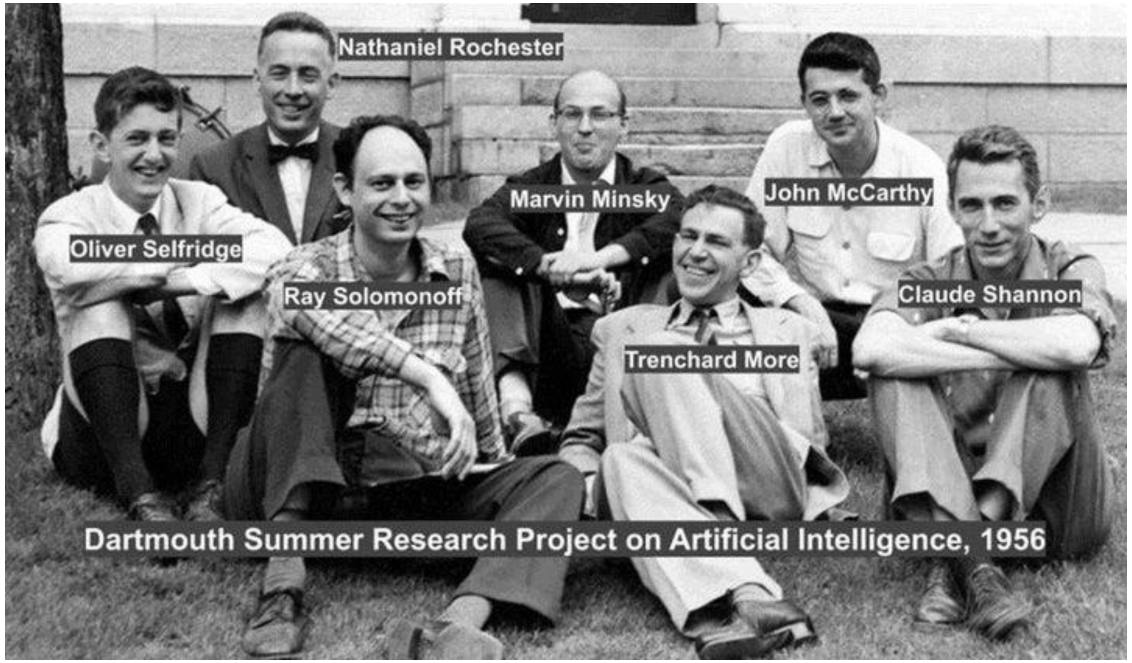
1952: Arthur Samuel

- Coined the term “**Machine Learning**” to describe systems that improve over time
- Developed the **first machine learning algorithms** to play the board game ***checkers***
- **Learning from experience** (1959 version)
  The program improved by playing games against itself
- In 1962, his program beat a human checker champion.
- Inspired key concepts in **reinforcement learning**, where agents learn by interacting with their environment



1956: The Dartmouth Workshop

- Explore how machines can simulate human intelligence
- Organized by John **McCarthy**, Marvin **Minsky**, Nathaniel **Rochester**, and Claude **Shannon**
- The term "**Artificial Intelligence**" was coined at this conference
- Marked **the birth of AI** as a formal field of study



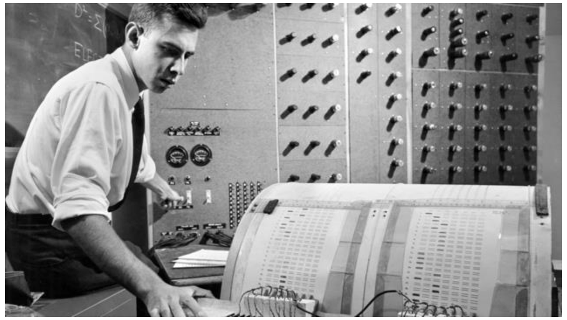
1957: Rosenblatt's perceptron

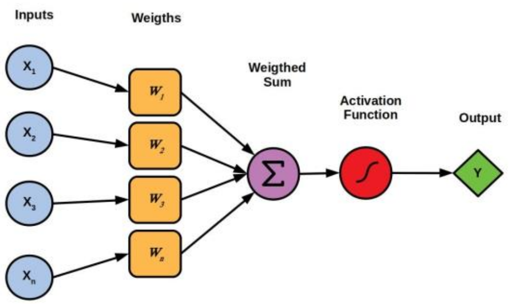
Single-layer perceptron:

Inspired by the MCP model, with only input and output layers

Advances by Rosenblatt

- Introduced a practical learning mechanism: weights can be adjusted automatically based on errors (learning from data)
- Later he built the first physical perceptron machine
- Demonstrated its use for image classification tasks





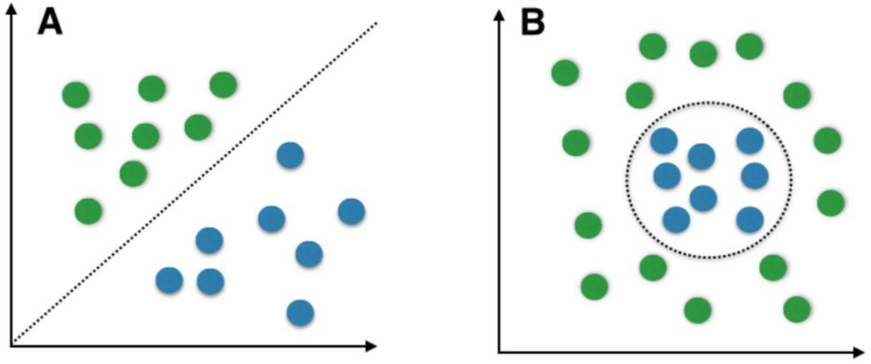
learning rate ("eta")

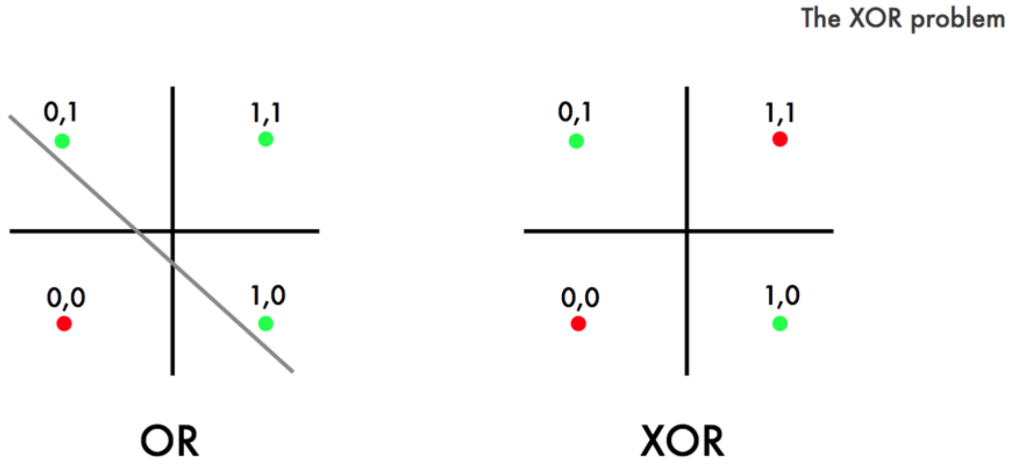
$$w_i^{n+1} = w_i^n + \eta(y_i - \hat{y}_i)x_i$$

new weight current weight

$\eta = 0.1$

Limitations of perceptron

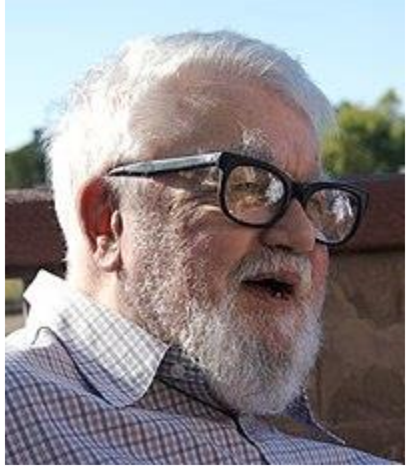




- Can only handle **linearly separable data**
  For example, it cannot be used to represent the XOR logical function
- **Single-layer** perceptron lack the capacity to represent complex relationships between inputs
- This problem was addressed later with **multi-layer perceptron (MLP)** and the backpropagation algorithm, enabling neural networks to solve nonlinear problems

1958: LISP Programming Language

- **LIS**T **P**rocessing (**LISP**)
- Developed by John **McCarthy** at MIT
- One of the oldest high-level programming languages still in use today
- **Designed specifically for artificial intelligence**
- Inspired modern languages like Python, R, Julia
- Widely used in early AI projects, expert systems, and symbolic computation



```
(defun make-perceptron (n m &optional (g  #'(lambda (i) (step-function 0 i)))
    &aux (l nil))

    (dotimes (i m (list l))
        (push (make-unit :parents (iota (1+ n))
            :children nil
            :weights (random-weights (1+ n) -0.5 +0.5)
            :g g)
        l)))
```

1960: Henry Kelley's backpropagation

- Introduced the concept of **backpropagation** in the context of control theory

- Used the **chain rule** of calculus to calculate gradients for optimizing functions

- Laid the foundation for modern deep neural networks:
  - Later adopted and extended by **Hinton et al.** to train multi-layer neural networks

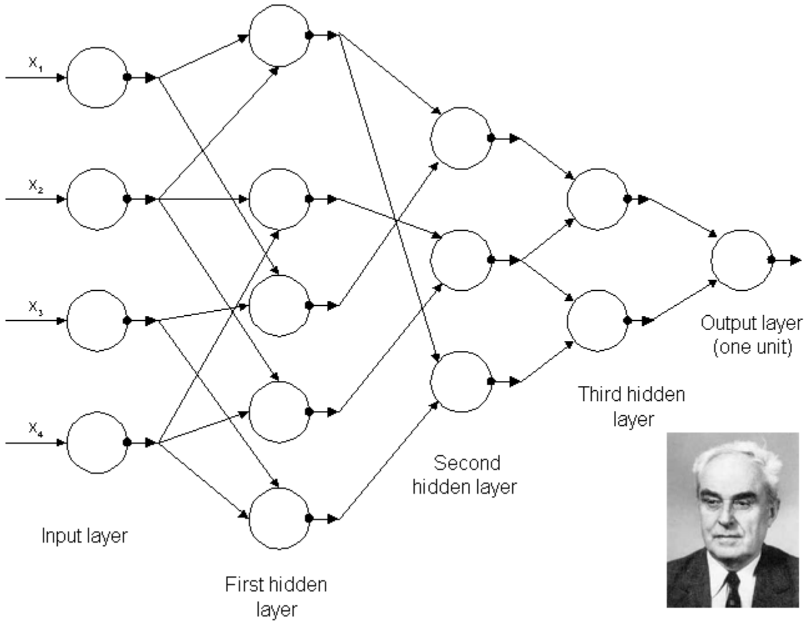
Gradient Theory of Optimal Flight Paths

HENRY J. KELLEY[1]

Grumman Aircraft Engineering Corp.
Bethpage, N. Y.

An analytical development of flight performance optimization according to the method of gradients or "method of steepest descent" is presented. Construction of a minimizing sequence of flight paths by a stepwise process of descent along the local gradient direction is described as a computational scheme. Numerical application of the technique is illustrated in a simple example of orbital transfer via solar sail propulsion. Successive approximations to minimum time planar flight paths from Earth's orbit to the orbit of Mars are presented for cases corresponding to free and fixed boundary conditions on terminal velocity components.

1965: Multi-layer perceptron

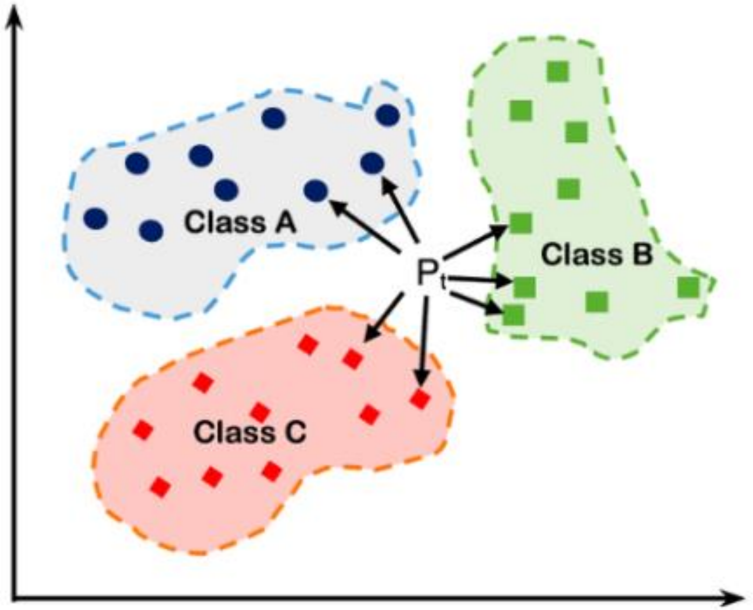


- **Alexey Ivakhnenko** built the first deep learning network, a multi-layered perceptron that could learn and adjust weights
- Demonstrated its use in solving complex regression problems
- Wasn't widely recognized at that time

1967: Nearest Neighbor algorithm

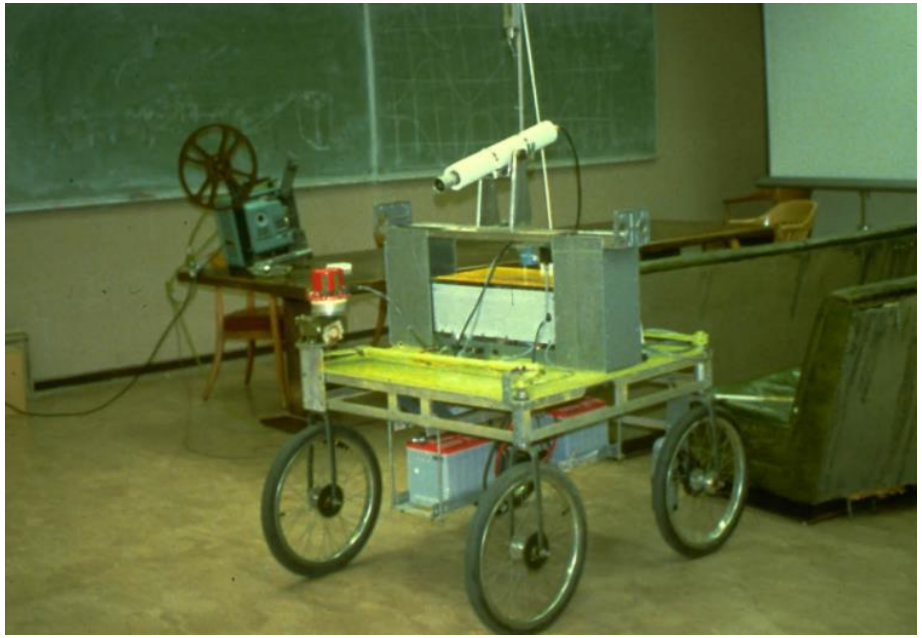
- Developed by **Cover and Hart** for pattern classification
- Introduced as a **supervised learning algorithm**
- **Key concept**: classify data based on the distance between features, often using Euclidian distance
- One of the simplest machine learning algorithms
- Forms the basis for modern instance-based learning methods

K Nearest Neighbors



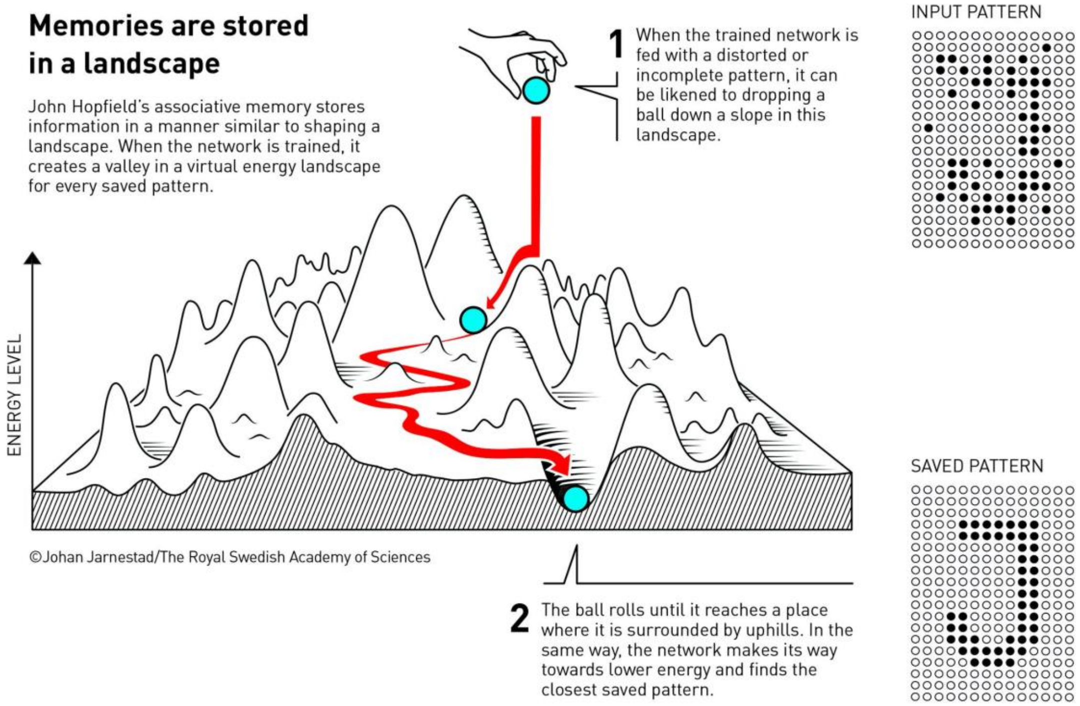
1979: Stanford Cart

- One of the first **autonomous vehicles**, developed by Stanford researchers
- Designed to navigate obstacles in a room **using computer vision**
- Moved very slowly, takes about **5 hours to traverse a room**
- Used a simple **stereo camera system** to analyze its environment
- Pioneered the concepts of **robotic autonomy** and **pathfinding algorithms**
- Key milestone in robotics and autonomous systems

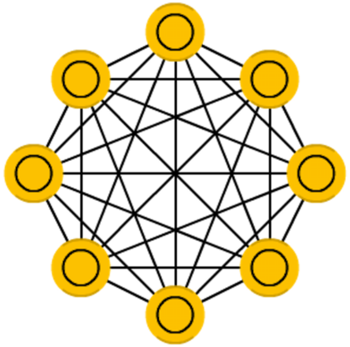


1982: Hopfield neural network

- Introduced by **John Hopfield** as a form of a recurrent neural network
- Designed to function as a **content-addressable memory** system: retrieves stored information based on incomplete or noisy input
- **A fully connected network** where each neuron is connected to all others
- Used in optimization problems and associative memory tasks

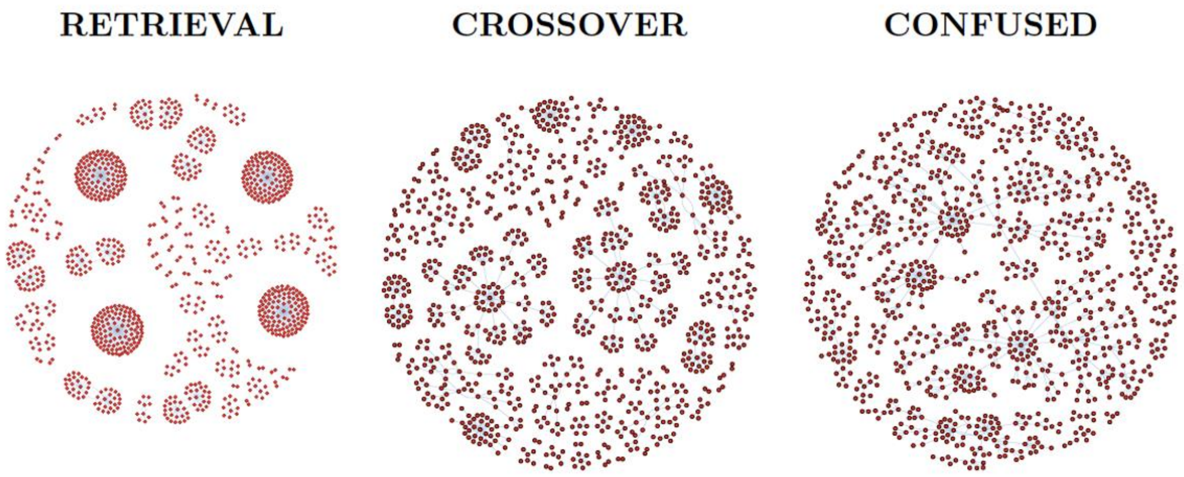


Hopfield neural network



- Energy of the Hopfield net

- Memories could be energy minima of a neural network



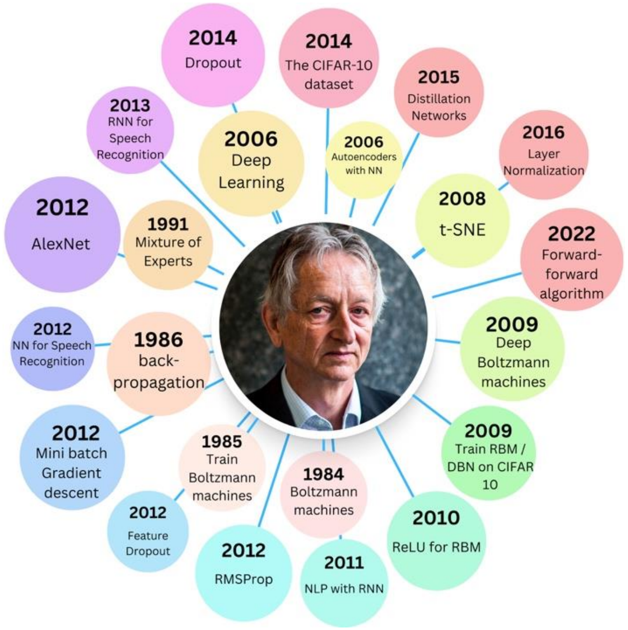
- **Storage capacity of the Hopfield network**

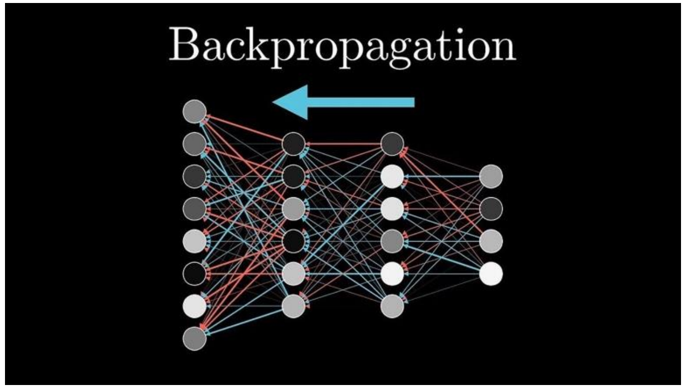
$$\alpha = \frac{K}{N}$$

- K patterns
- N neurons or spins

1986: Backpropagation for DL

- Introduced by Geoffrey **Hinton**, David **Rumelhart**, and Ronald **Williams**
- Enabled training of multi-layer neural networks (deep neural networks)
  - ❑ Uses the chain rule of calculus to calculate gradients for all layers
  - ❑ Gradients are used to adjust weights to minimize the error (or loss function)
- Solved the **XOR problem** and other nonlinear classification problems
- Marked a turning point in the revival of neural networks and paved the way for modern deep learning (DL)






NOBELPRISET I FYSIK 2024
THE NOBEL PRIZE IN PHYSICS 2024
KUNGL. VETENSKAPS-AKADEMIEN
THE ROYAL SWEDISH ACADEMY OF SCIENCES
John J. Hopfield
Princeton University, NJ, USA
Geoffrey E. Hinton
University of Toronto, Canada
"för grundläggande upptäckter och uppfinningar som möjliggör maskininlärning med artificiella neuronnätverk"
"for foundational discoveries and inventions that enable machine learning with artificial neural networks"

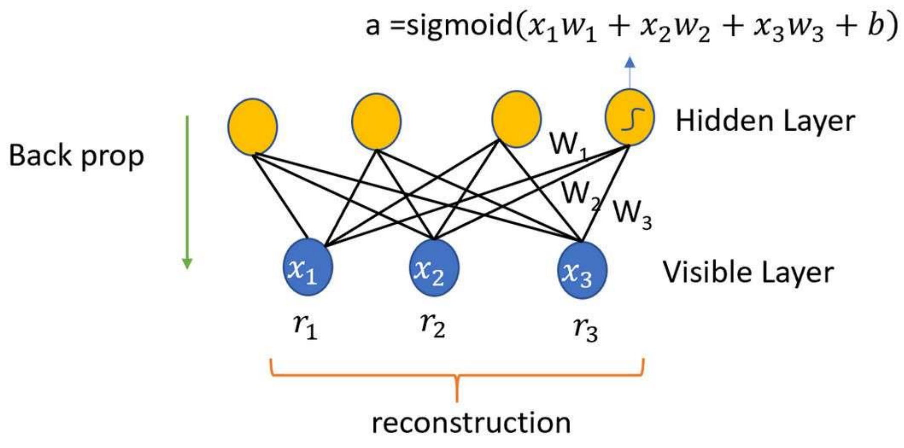
1986: Restricted Boltzmann machine (RBM)

- Introduced by: **Paul Smolensky**

- A **generative stochastic neural network**
  - ❑ Learns a probability distribution over its input data

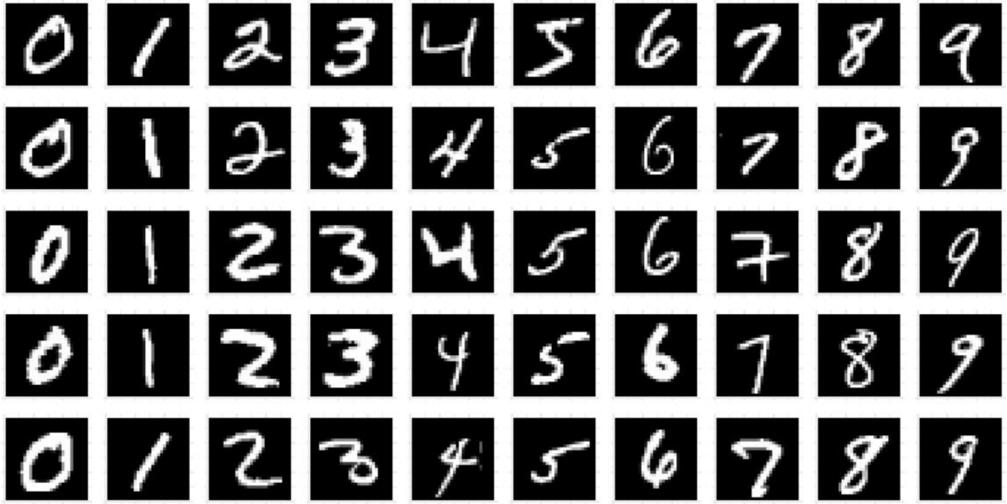
- **Applications**
  - ❑ Dimensionality reduction
  - ❑ Classification and regression
  - ❑ Collaborative filtering (e.g., recommendation systems)
  - ❑ Feature learning and topic modeling

- Inspired later advancements like **Deep Belief Networks (DBNs)**



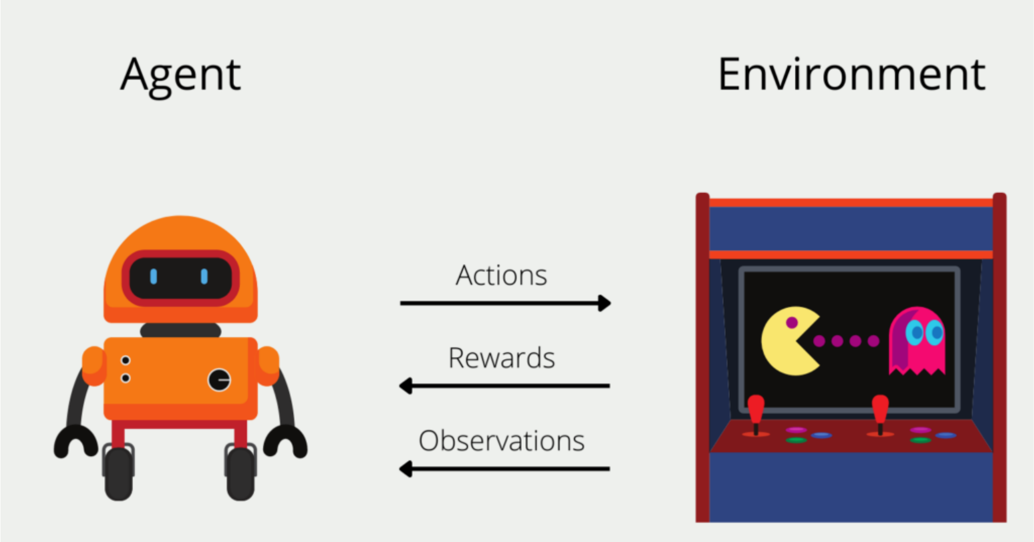
1989: Yann LeCun and Digit recognition

- Developed one of the first practical **deep neural networks** for recognizing handwritten digits
- Used the **convolutional neural network (CNN)** architecture
- Trained on the **MNIST dataset**, a benchmark for image recognition
- Introduced the combination of backpropagation and weight optimization for multi-layer networks
- Significant for laying the foundation of modern computer vision applications, such as OCR (Optical Character Recognition)



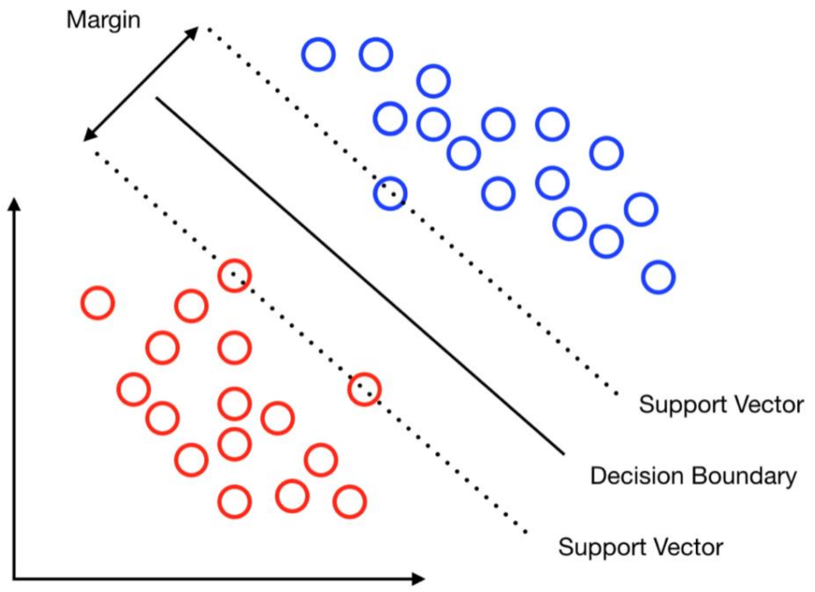
1989: Q-learning

- Proposed by **Christopher Watkins**
- A model-free **reinforcement learning** algorithm
- Learns an optimal action-selection policy for **an agent interacting with its environment**
- Key innovation: uses a **Q-value** to evaluate state-action pairs
- **Update rule**: The Q-value is updated using the reward received and the maximum future Q-value
- **Applications**: Robotics, game AI, and autonomous systems



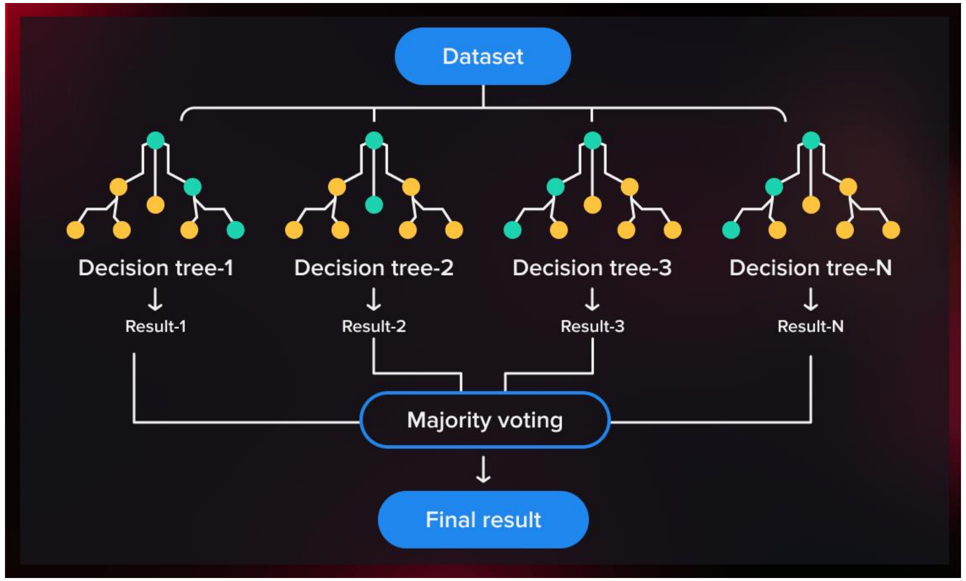
1995: Support Vector Machine (SVM)

- Developed by **Vladimir Vapnik** and **Corinna Cortes**
- A supervised learning algorithm for classification and regression tasks
- Key idea: finds the **optimal hyperplane** that separates data into classes with the **maximum margin**
- Supports **kernel functions** to handle nonlinearly separable data
- Applications: text classification, image recognition, and bioinformatics



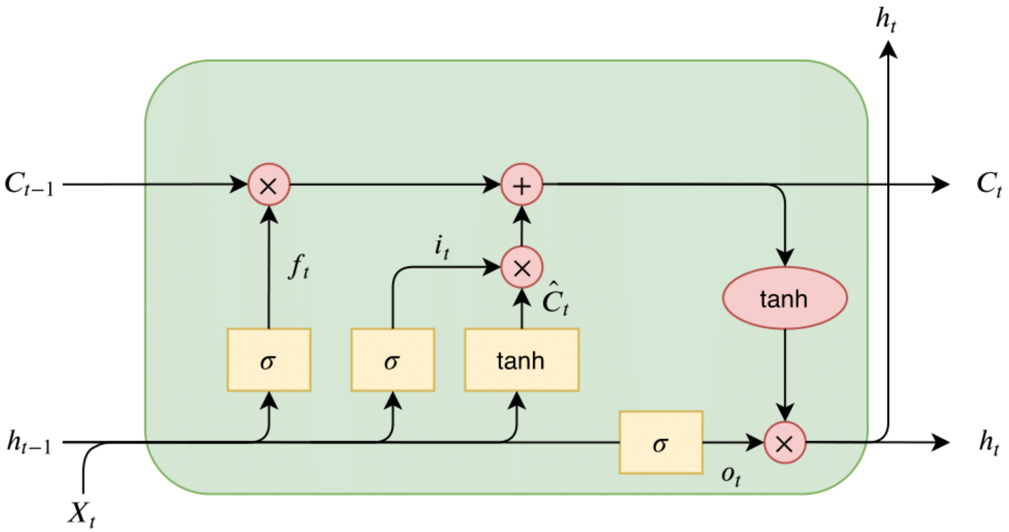
1995: Random Decision Forest

- Introduced by **Tin Kam Ho**
- **Ensemble learning method** that combines multiple decision trees to improve accuracy and reduce overfitting
- Uses **random sampling** of data (bagging) and features to build diverse trees
- Outputs are aggregated (e.g., **majority vote** for classification or averaging for regression)
- **Advantages**: High accuracy, robustness to overfitting, and ability to handle large datasets with many features



1997: Long short-term memory (LSTM)

- Developed by **Sepp Hochreiter** and **Jurgen Schmidhuber**
- A type of **recurrent neural network (RNN)** designed to solve problem of **vanishing gradients**
- Introduced memory cells and gates (**inputs, forget, and output gates**) to control the flow of information
- Excels at processing **sequential data** and maintaining long-term dependencies
- Widely used for speech recognition, language modeling, machine translation, and time-series analysis

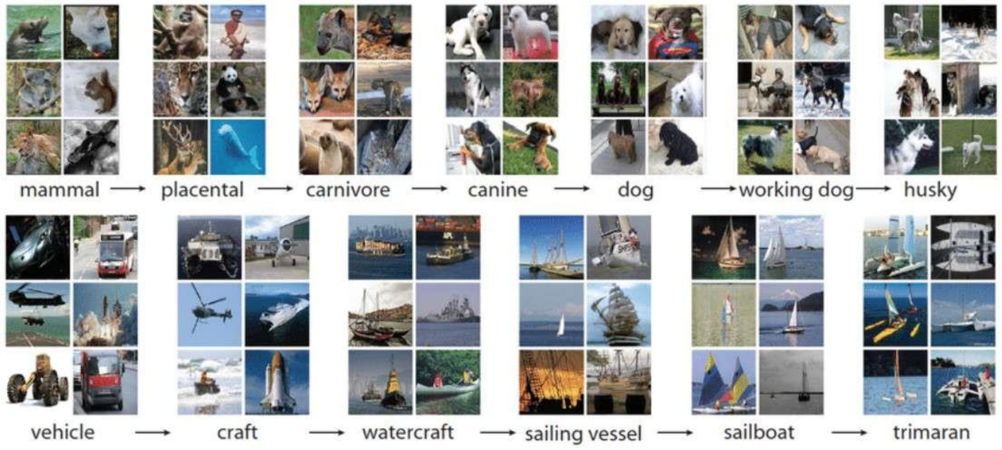


1997: Deep Blue defeats Garry Kasparov

- **IBM's** Deep Blue became the first computer to defeat a reigning world **chess** champion in a match
- Used a combination of **brute-force search algorithms** and **domain-specific heuristics** to evaluate millions of possible moves
- Demonstrated the power of specialized AI in solving complex, rule-based problems
- Inspired further research into game-playing AI and advanced decision-making systems

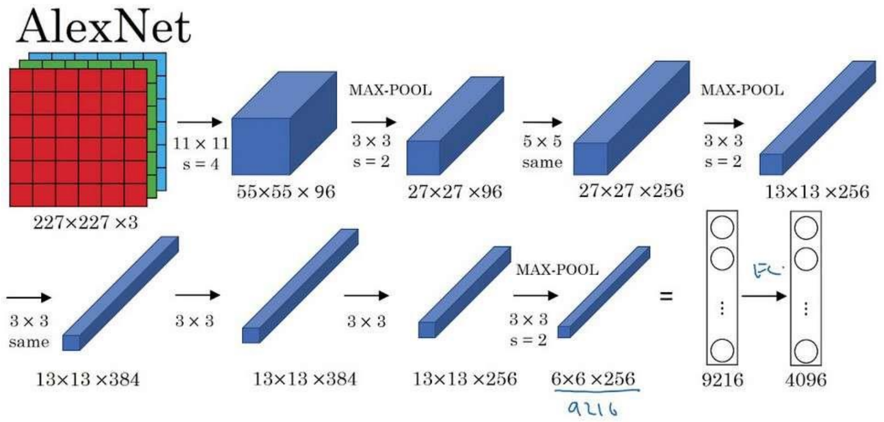
2009: ImageNet

- Launched by **Fei-fei Li** and her team at **Stanford** University
- A **large-scale image dataset** designed to advance computer vision research
- Contains over **14 million labeled images** across thousands of categories
- Introduced the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2010
- Played a key-role in the rise of deep-learning and breakthroughs in image classification
- Enabled models like AlexNet, ResNet, and beyond



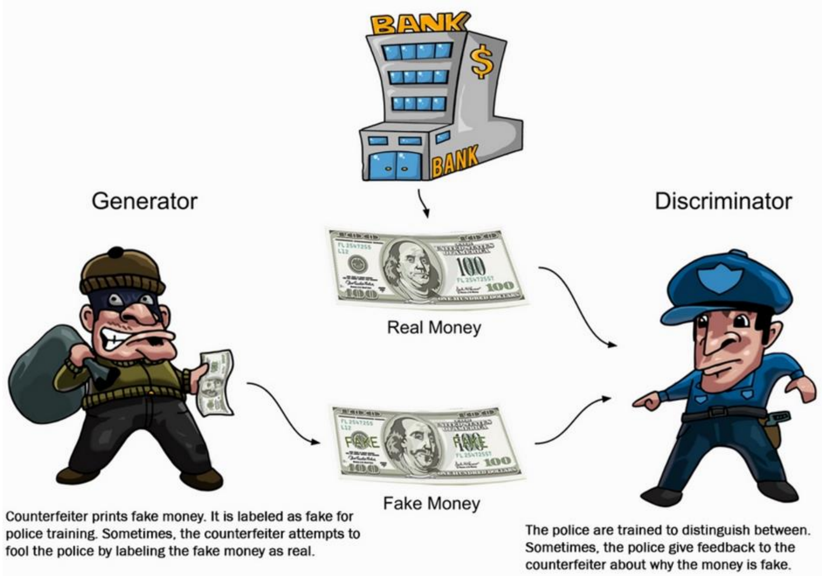
2012: AlexNet

- Developed by **Alex Krizhevsky, Ilya Sutskever**, and **Geoffrey Hinton**
- Won **the ImageNet Large Scale Visual Recognition Challenge (ILSVRC)** with a top-5 error rate of **15.3%** (far surpassing the runner-up's 26.2%)
- Introduced a **deep convolutional neural network** (CNN) architectures with **8 layers**
- Key renovations:
  - **ReLU activation function**: improved training efficiency
  - **Dropout regularization**: reduced overfitting
  - Leveraged GPUs for faster training on large datasets



2014: Generative Adversarial Networks (GANs)

- Introduced by **Ian Goodfellow** and collaborators
- A framework consisting of two neural networks:
  - ❑ **Generator**: creates fake data (e.g., images)
  - ❑ **Discriminator**: Distinguishes between real and fake data
- The two networks compete, improving each other through an adversarial process
- Applications:
  - ❑ Generating realistic images, videos, music.
  - ❑ Data augmentation, style transfer, and deepfake generation
  - ❑ Advancing scientific research in drug discovery and simulation
- Mark a major leap **in unsupervised learning** and generative AI



2014: DeepFace

- Developed by **Facebook's** AI research team
- A **deep learning-based facial recognition system**
- Achieved **97.35% accuracy** in facial recognition, similar to human performance
- Used a **deep convolutional neural network (CNN**) architecture to map faces into a compact embedding space
- Revolutionized facial recognition applications in social media and beyond

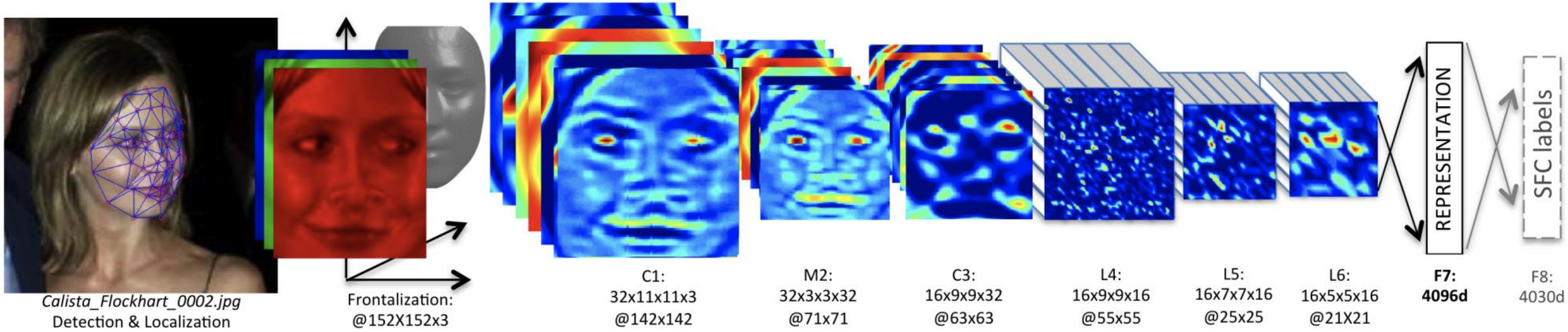


Figure 2. **Outline of the *DeepFace* architecture**. A front-end of a single convolution-pooling-convolution filtering on the rectified input, followed by three locally-connected layers and two fully-connected layers. Colors illustrate feature maps produced at each layer. The net includes more than 120 million parameters, where more than 95% come from the local and fully connected layers.

2014: Eugene Goostman Chatbot

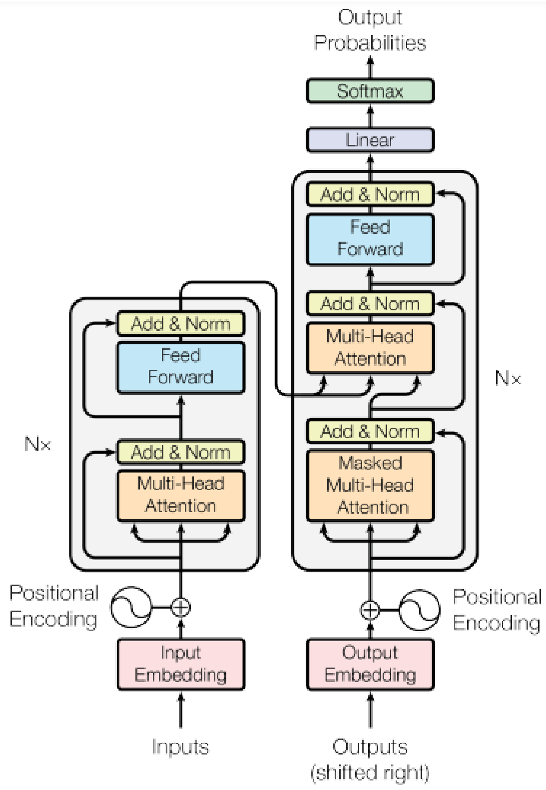
- Created by **Vladimir Veselov** and **Eugene Demchenko**
- Portrayed a **13-year-old Ukranian boy** to simulate personality and imperfections
- In 2014, it **passed the Turing Test**, convincing 33% of judges that it was human.
- The chatbot used **natural language processing (NLP)** techniques and clever conversational strategies
- Sparked a debate about the validity of the Turing Test as a measure of machine intelligence

2016: AlphaGo

- Developed **by Google's DeepMind**
- First AI to defeat a professional human player at the board gam **Go**.
- Achieved a historic victory against **Lee Sedol**, a 9-dan Go champion, with a 4-1 score
- Combined **deep neural network** and **reinforcement learning** to master the complexity strategy of Go
- Go's immense complexity (more possible board states than atoms in the universe) made it a long-standing AI challenge
- Marked a leap in **game-playing AI** and inspired advancements in other fields like protein folding and optimization

2017: Transformer

- Introduced in the paper "**Attention is all you need**"
- Replaced traditional recurrent architectures (e.g., RNNs, LSTMs) for sequential data processing)
- Key innovation: **Self-Attention Mechanism**, allowing the model to focus on relevant parts of input data
- Enabled parallelization, making training faster and more efficient
- Revolutionized **natural language processing (NLP)**: machine translation, text summarization, and question answering
- Foundation for models like **BERT**, **GPT**, and **ChatGPT**



Attention Is All You Need

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2018: BERT

- **Google** introduced **BERT (Bidirectional Encoder Representation from Transformers)**
- Pre-trained Transformer-based model for **natural language processing (NLP)**
- Key innovation: Processes text **bidirectionally**, capturing context from both sides of a word
- Revolutionized NLP tasks

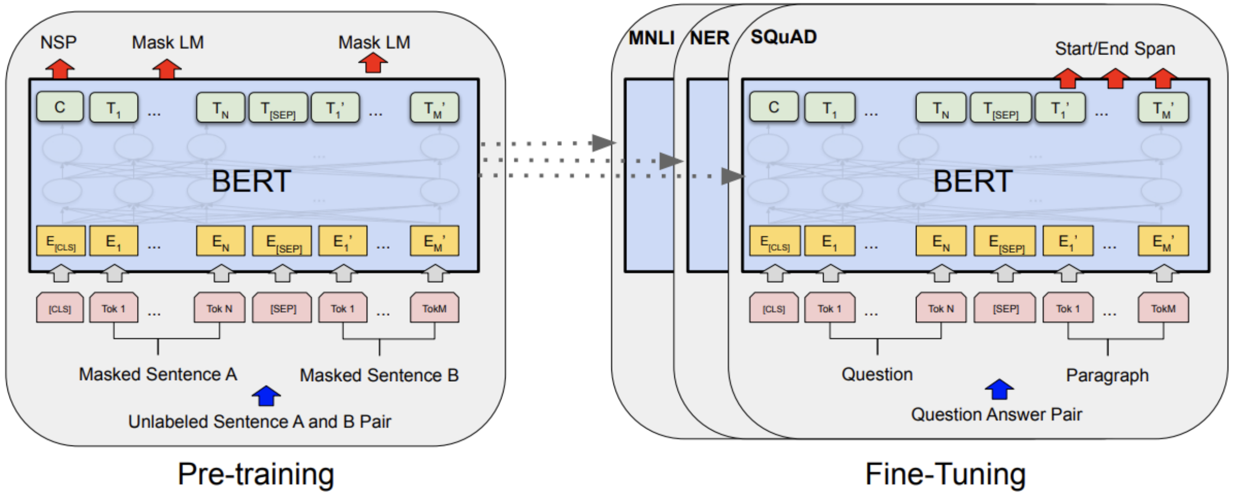
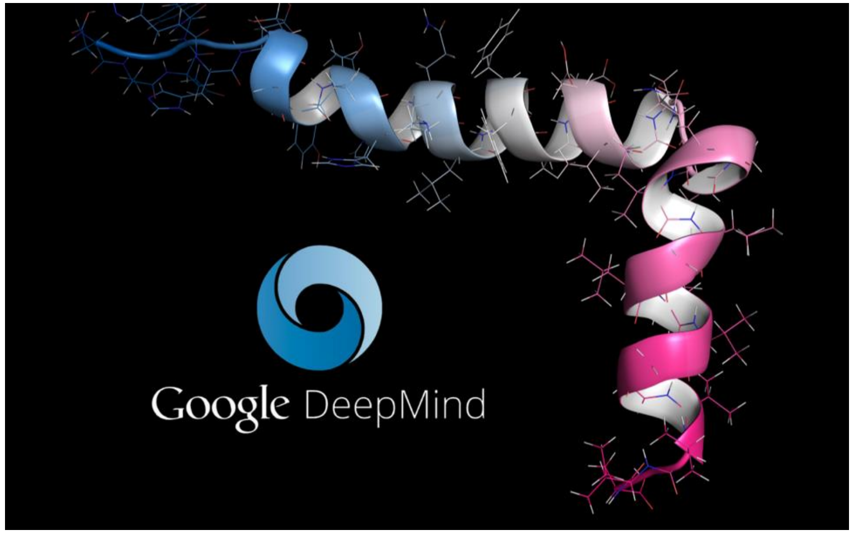


Figure 1: Overall pre-training and fine-tuning procedures for BERT. Apart from output layers, the same architectures are used in both pre-training and fine-tuning. The same pre-trained model parameters are used to initialize

2020: AlphaFold

- Developed by Google's DeepMind
- Revolutionized protein structure prediction
- Solved a 50-year challenge in molecular biology: predicting 3D protein structures from amino acid sequences
- Leveraged deep learning to achieve unparalleled accuracy in the CASP14 competition, outperforming traditional methods
- Applications: drug discovery and design; understanding diseases at the molecular level; advancing fields like synthetic biology and bioengineering



2018-2024: OpenAI's ChatGPT

- **2018**: OpenAI introduced the **GPT (Generative Pre-trained Transformer)** architecture

- **2020**: Released **GPT-3**, with 175 billion parameters

- **2022**: Introduced **ChatGPT**, a conversational AI fine-tuned from GPT-3.5, capable of context-aware dialogues

- **2024**: Ongoing advancements in GPT-4 and beyond, focusing on **multimodal capabilities** (text, images, and more)

- Widely adopted for tasks like customer support, content creation, coding, and education

- Raising discussions around ethics, biases, and AI's societal impact

2025: DeepSeek

Bloomberg the Company & Its Products | Bloomberg Terminal Demo Request | Bloomberg Anywhere Remote Login | Bloomberg Customer Support

Bloomberg

Chunlei

Live TV | Markets | Economics | Industries | Tech | Politics | Businessweek | Opinion | More | US Edition

Top Securities | S&P 500 6,012.28 ▼1.46% | Nasdaq 19,341.84 ▼3.07% | US 10 Yr 4.55 ▼0.10% | FTSE 100 8,503.71 ▲0.02% | Crude Oil 73.12 ▼0.07% | Gold 2.

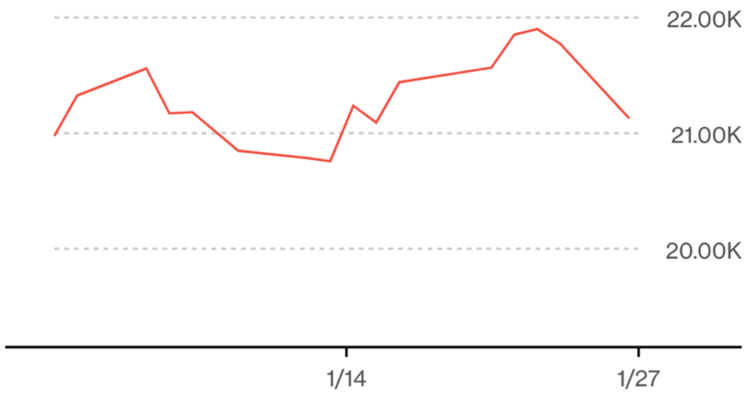
AI-Fueled Stock Rally Dealt $1 Trillion Blow by Chinese Upstart

Overnight Fame Strains DeepSeek's Systems, Draws Attacks

Nvidia Calls DeepSeek 'Excellent' AI Advance, Dismisses Concerns

World's Richest People Lose $108 Billion After Tech Selloff

Nasdaq 100 Falls
21,127.28 USD ▼646.73 -2.97%



Andrey Rudakov/Bloomberg

The Big Take

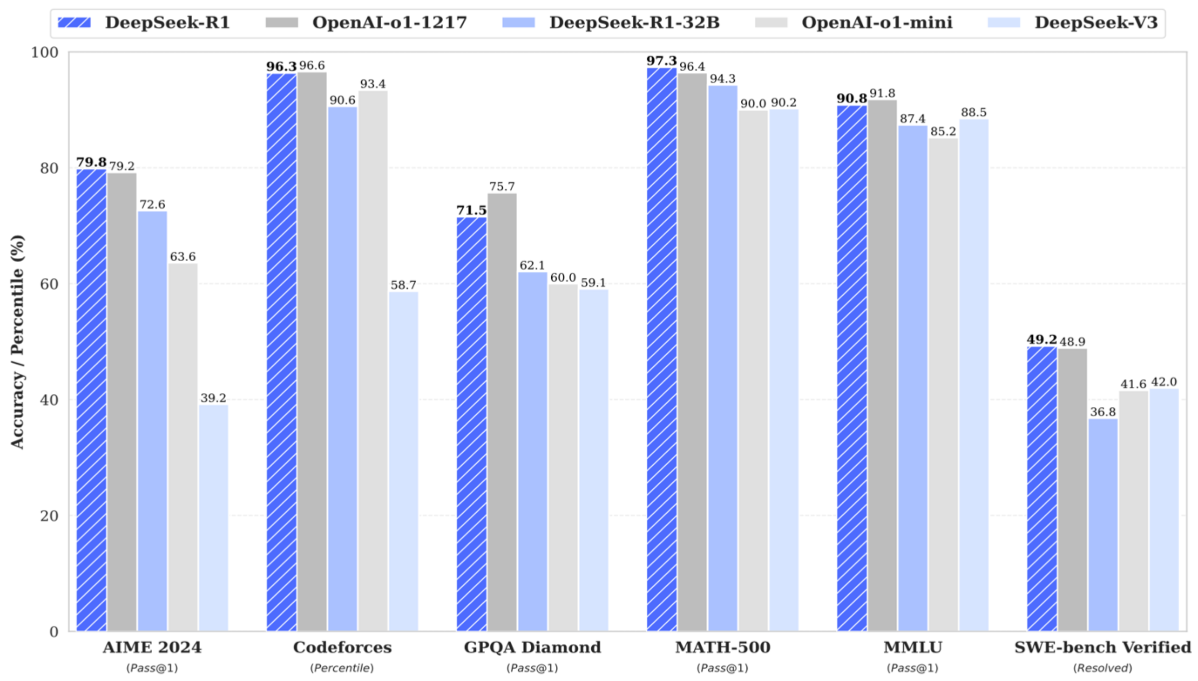
DeepSeek Challenges Everyone's Assumptions About AI Costs

The Chinese upstart says its rival to ChatGPT comes at a fraction of the cost, raising questions about the rationale for stratospheric AI budgets.

2025: DeepSeek

arXiv: 2501.12948

DeepSeek-R1: Incentivizing Reasoning Capability in LLMs via Reinforcement Learning



Abstract

We introduce our first-generation reasoning models, DeepSeek-R1-Zero and DeepSeek-R1. DeepSeek-R1-Zero, a model trained via large-scale reinforcement learning (RL) without supervised fine-tuning (SFT) as a preliminary step, demonstrates remarkable reasoning capabilities. Through RL, DeepSeek-R1-Zero naturally emerges with numerous powerful and intriguing reasoning behaviors. However, it encounters challenges such as poor readability, and language mixing. To address these issues and further enhance reasoning performance, we introduce DeepSeek-R1, which incorporates multi-stage training and cold-start data before RL. DeepSeek-R1 achieves performance comparable to OpenAI-o1-1217 on reasoning tasks. To support the research community, we open-source DeepSeek-R1-Zero, DeepSeek-R1, and six dense models (1.5B, 7B, 8B, 14B, 32B, 70B) distilled from DeepSeek-R1 based on Qwen and Llama.

Reinforcement learning algorithm

Group Relative Policy Optimization In order to save the training costs of RL, we adopt Group Relative Policy Optimization (GRPO) (Shao et al., 2024), which foregoes the critic model that is typically the same size as the policy model, and estimates the baseline from group scores instead. Specifically, for each question q, GRPO samples a group of outputs $\{o_1, o_2, \cdots, o_G\}$ from the old policy $\pi_{\theta_{old}}$ and then optimizes the policy model π_θ by maximizing the following objective:

$$\mathcal{J}_{GRPO}(\theta) = \mathbb{E}[q \sim P(Q), \{o_i\}_{i=1}^{G} \sim \pi_{\theta_{old}}(O|q)]$$
$$\frac{1}{G}\sum_{i=1}^{G}\left(\min\left(\frac{\pi_\theta(o_i|q)}{\pi_{\theta_{old}}(o_i|q)}A_i, \text{clip}\left(\frac{\pi_\theta(o_i|q)}{\pi_{\theta_{old}}(o_i|q)}, 1-\varepsilon, 1+\varepsilon\right)A_i\right) - \beta\mathbb{D}_{KL}\left(\pi_\theta||\pi_{ref}\right)\right), \quad (1)$$

$$\mathbb{D}_{KL}\left(\pi_\theta||\pi_{ref}\right) = \frac{\pi_{ref}(o_i|q)}{\pi_\theta(o_i|q)} - \log\frac{\pi_{ref}(o_i|q)}{\pi_\theta(o_i|q)} - 1, \quad (2)$$

where ε and β are hyper-parameters, and A_i is the advantage, computed using a group of rewards $\{r_1, r_2, \ldots, r_G\}$ corresponding to the outputs within each group:

$$A_i = \frac{r_i - \text{mean}(\{r_1, r_2, \cdots, r_G\})}{\text{std}(\{r_1, r_2, \cdots, r_G\})}. \quad (3)$$