Introduction to Artificial Intelligence

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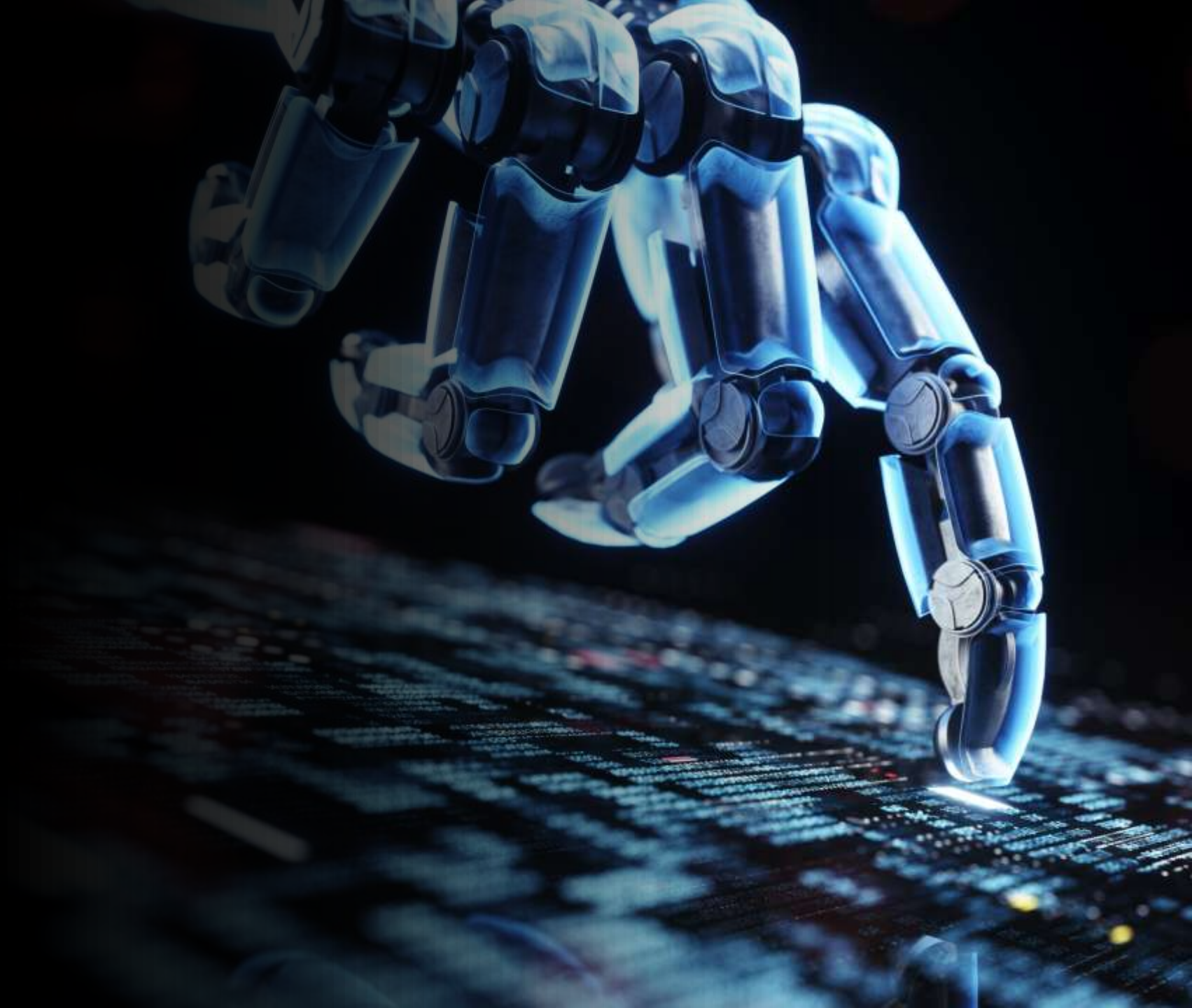
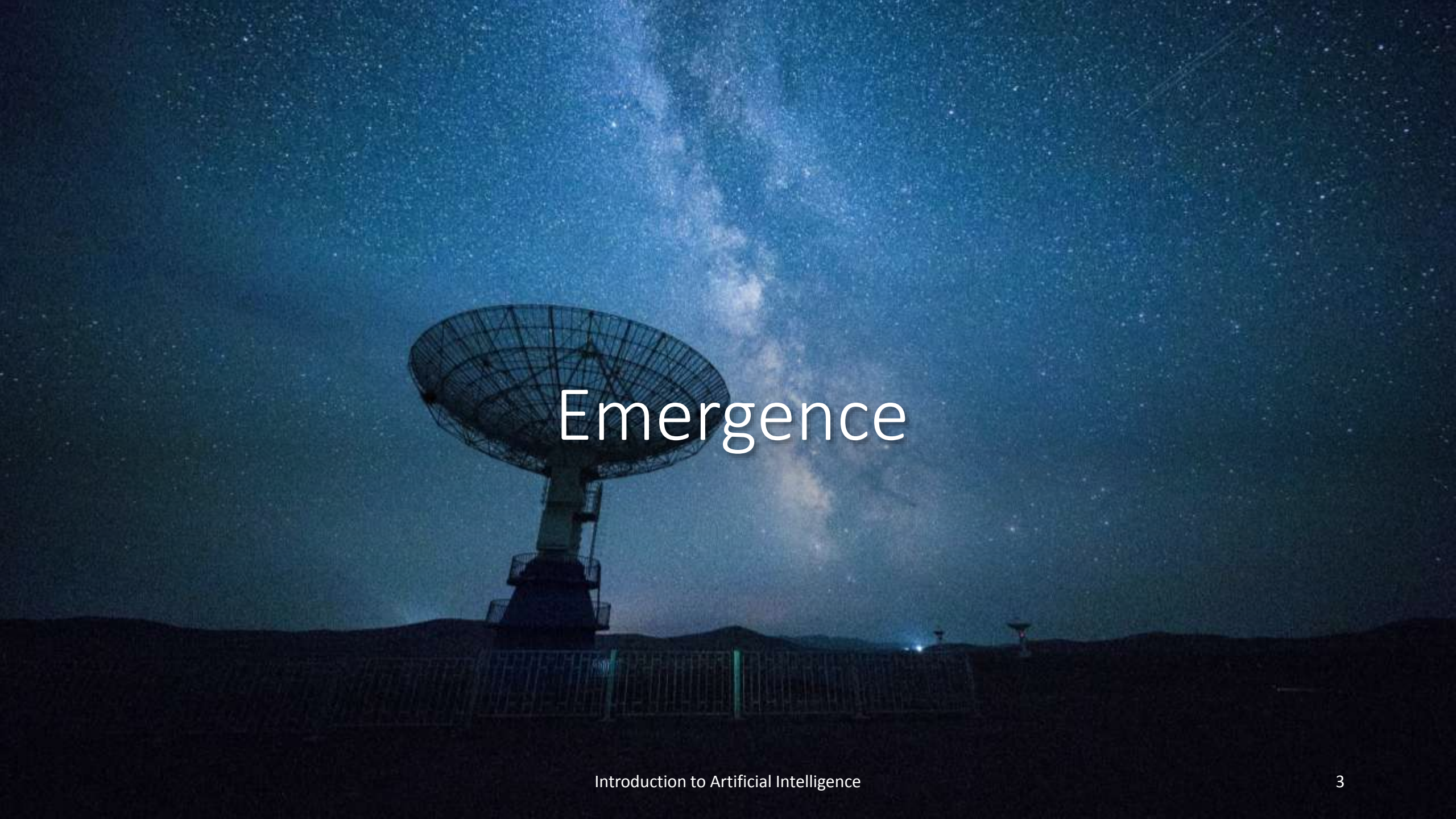
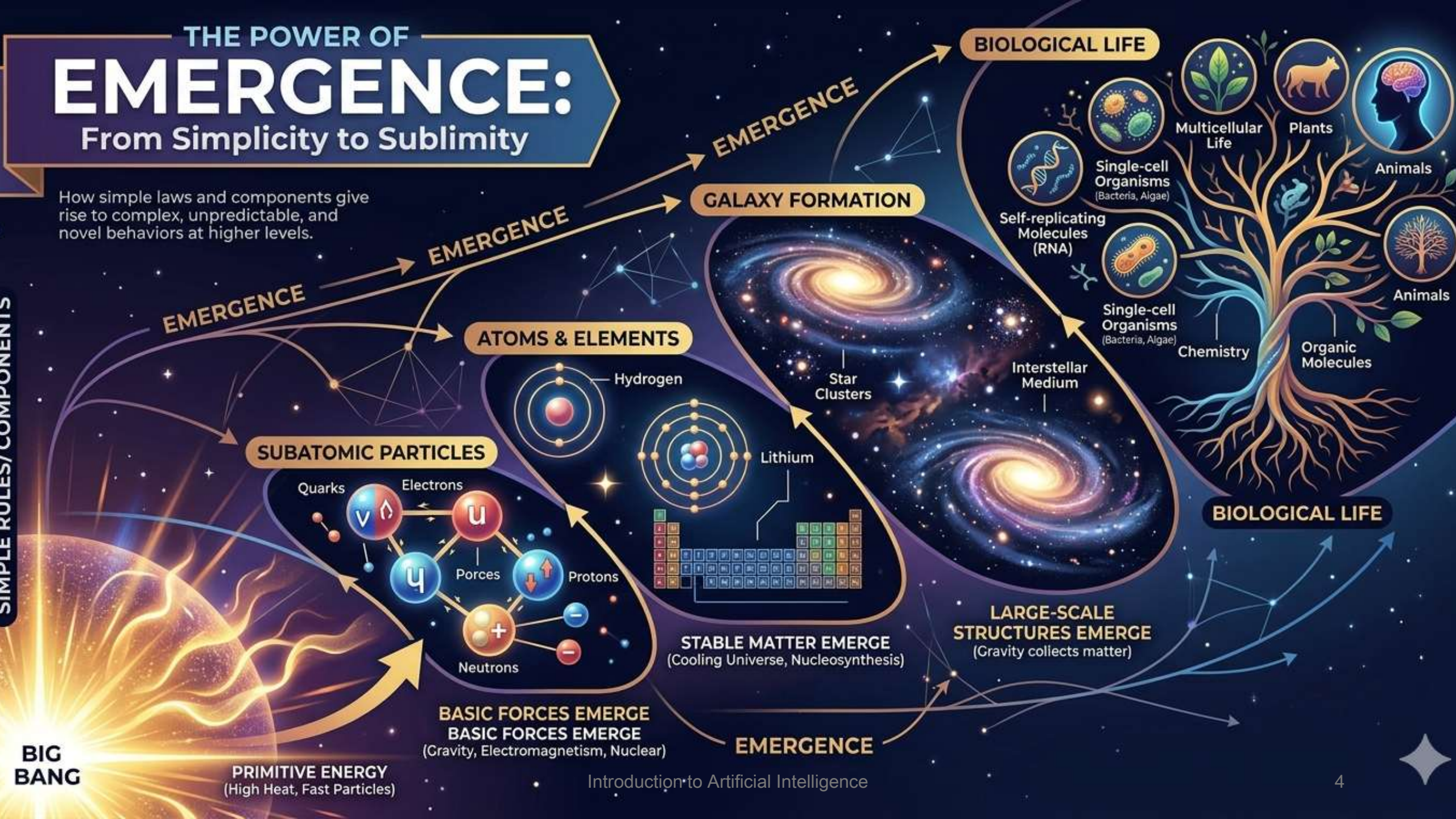
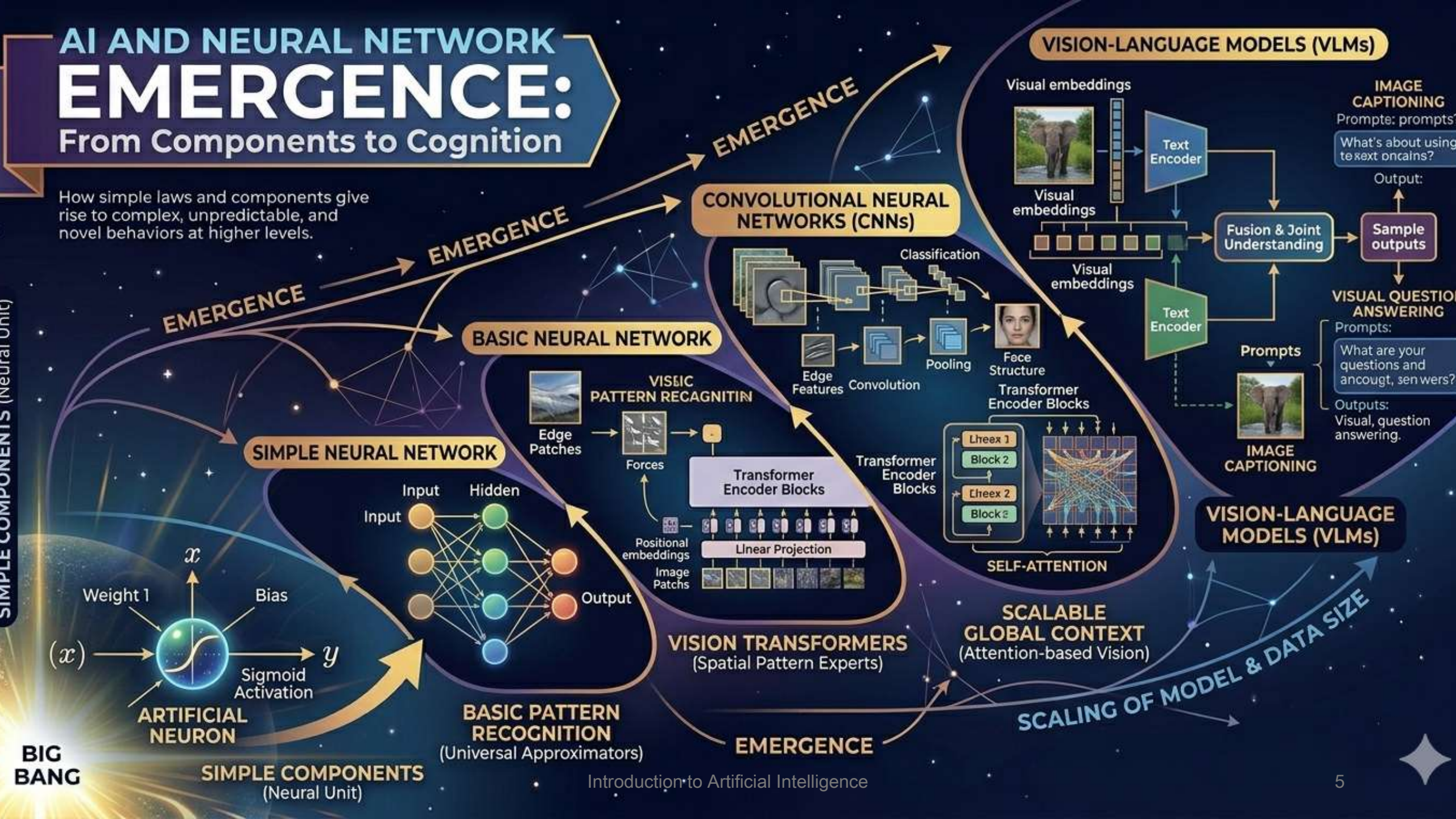


Course Outline

- Emergence
- From Turing to LLMs
- The Evolution of AI
- Isn’t AI just another program?
- Symbolic vs. Connectionist AI
- The AI Project Lifecycle
- Learning Paradigms
- Ethics & Bias
- Challenges
- Current Trends


Emergence


THE POWER OF
EMERGENCE:
From Simplicity to Sublimity
How simple laws and components give rise to complex, unpredictable, and novel behaviors at higher levels.
SIMPLE RULES/COMPONENTS
EMERGENCE
EMERGENCE
EMERGENCE
EMERGENCE
BIOLOGICAL LIFE
Multicellular Life
Plants
Animals
Single-cell Organisms (Bacteria, Algae)
Self-replicating Molecules (RNA)
Single-cell Organisms (Bacteria, Algae)
Animals
Chemistry
Organic Molecules
BIOLOGICAL LIFE
GALAXY FORMATION
Star Clusters
Interstellar Medium
ATOMS & ELEMENTS
Hydrogen
Lithium
SUBATOMIC PARTICLES
Quarks
Electrons
Porces
Protons
Neutrons
STABLE MATTER EMERGE
(Cooling Universe, Nucleosynthesis)
LARGE-SCALE STRUCTURES EMERGE
(Gravity collects matter)
BASIC FORCES EMERGE
BASIC FORCES EMERGE
(Gravity, Electromagnetism, Nuclear)
EMERGENCE
BIG BANG
PRIMITIVE ENERGY
(High Heat, Fast Particles)

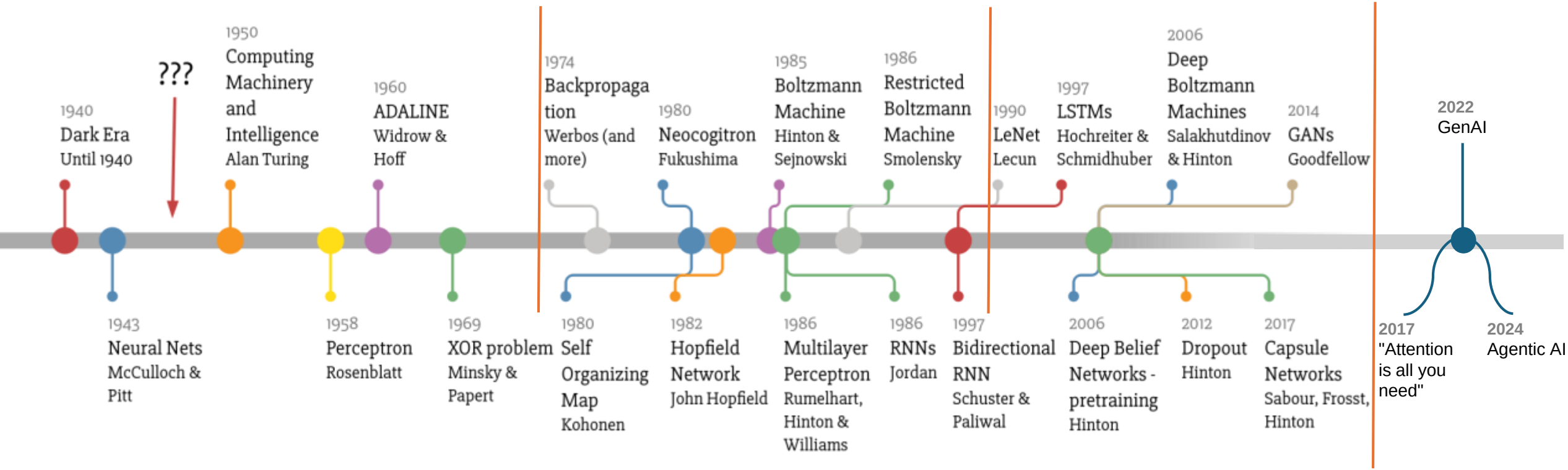

AI AND NEURAL NETWORK
EMERGENCE:
From Components to Cognition
How simple laws and components give rise to complex, unpredictable, and novel behaviors at higher levels.
EMERGENCE
EMERGENCE
EMERGENCE
EMERGENCE
SIMPLE COMPONENTS (Neural Unit)
BIG BANG
SIMPLE COMPONENTS
(Neural Unit)
ARTIFICIAL NEURON
Weight 1
Bias
Sigmoid Activation
SIMPLE NEURAL NETWORK
Input
Hidden
Output
BASIC PATTERN RECOGNITION
(Universal Approximators)
BASIC NEURAL NETWORK
Edge Patches
Forces
Positional embeddings
Image Patches
Transformer Encoder Blocks
Linear Projection
VISION TRANSFORMERS
(Spatial Pattern Experts)
CONVOLUTIONAL NEURAL NETWORKS (CNNs)
Classification
Edge Features
Convolution
Pooling
Face Structure
Transformer Encoder Blocks
Block 1
Block 2
Block 3
SELF-ATTENTION
SCALABLE GLOBAL CONTEXT
(Attention-based Vision)
VISION-LANGUAGE MODELS (VLMs)
Visual embeddings
Text Encoder
Visual embeddings
Fusion & Joint Understanding
Sample outputs
IMAGE CAPTIONING
Prompts:
Output:
Visual embeddings
Text Encoder
Prompts
IMAGE CAPTIONING
VISUAL QUESTION ANSWERING
Prompts:
What are your questions and answers?
Outputs:
Visual, question answering.
VISION-LANGUAGE MODELS (VLMs)
SCALING OF MODEL & DATA SIZE
EMERGENCE

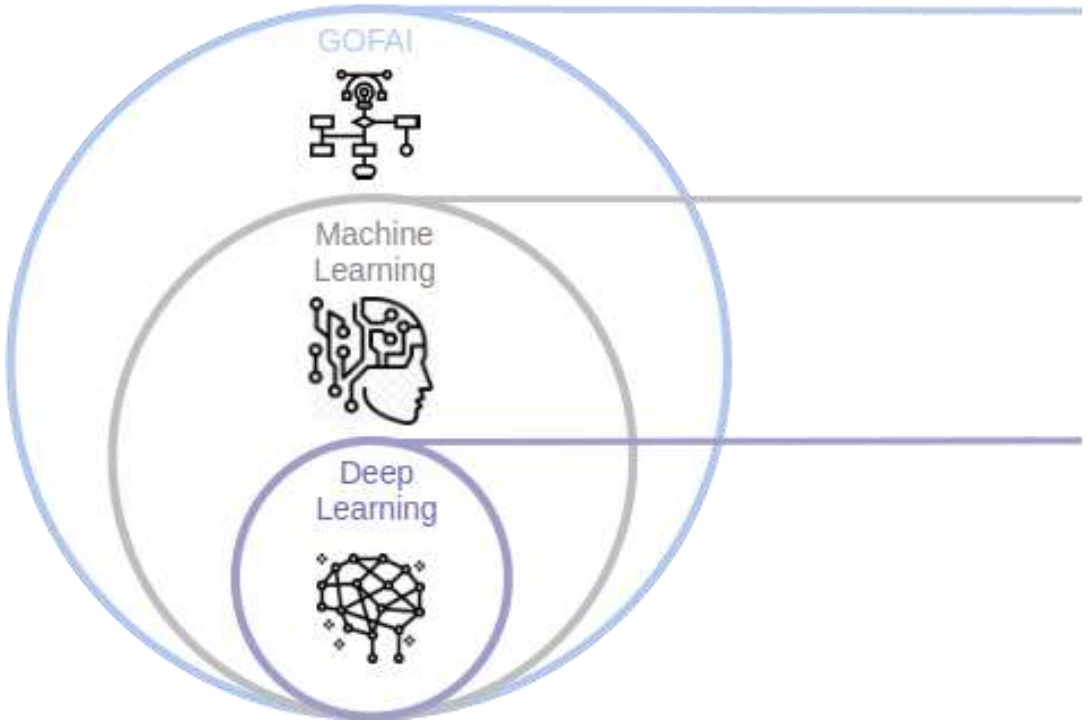
Intelligence – Fundamental Principles

An intelligent system is a **self-maintaining** system that **adaptively** regulates its interaction with the environment through a **plastic** perception-action loop, guided by intrinsic norms.

1. Self-organization
2. Adaptation
3. Learning

From Turing to LLMs





Rule-Based AI :
- propositional & predicate logic
- Rules + Knowledge base = Intelligence

Human & Machine collaboration:
- Manual feature extraction
- Step-by-step analysis
- Automatic ML classification

Biology Inspire:
- 100% data driven
- End-to-End
- Fully-automated analysis
- Millions of parameters

The Evolution of Artificial Intelligence

Isn’t AI just another program?

Feature	Traditional Programming	Artificial Intelligence (ML)
Logic	Hand-coded **rules**	**Learned patterns** from data
Flexibility	Rigid**,** only does what it's **told**	Adaptive, **generalize** on new data
Outcome	**Predictable** and repeatable	**Probabilistic** and **prognostic**
Best For	Browsing, accounting, basic **processing**	Image **analysis**, recognition, generation, image to text

Symbolic AI vs. Artificial Neural Network

	Symbolic AI	Artificial Neural Network
Logic	**If** A=B and B=C, **then** A=C	Adaptive **weights**
Structure	Data + Rules = **GOFAI**	Layers of **densely connected** neurons
Strength	**Explainable**	Partial information, noise, **complexity**
Weakness	Rule for **every** scenario	"Black Box"

Why Neural Networks Won the Race?

- **Big Data**
- **Hardware**
- "Low-level" intelligence
  - vision, speech, translation
  - **huge leap!**
- **Future**
  - Neuro-Symbolic AI?

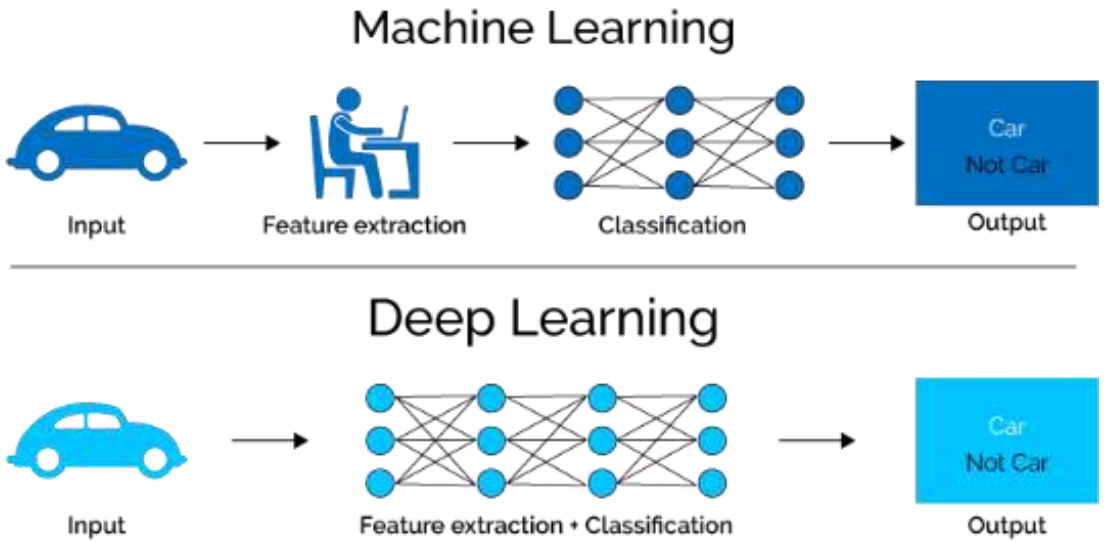
Data: The Engine of AI

Traditional Analysis

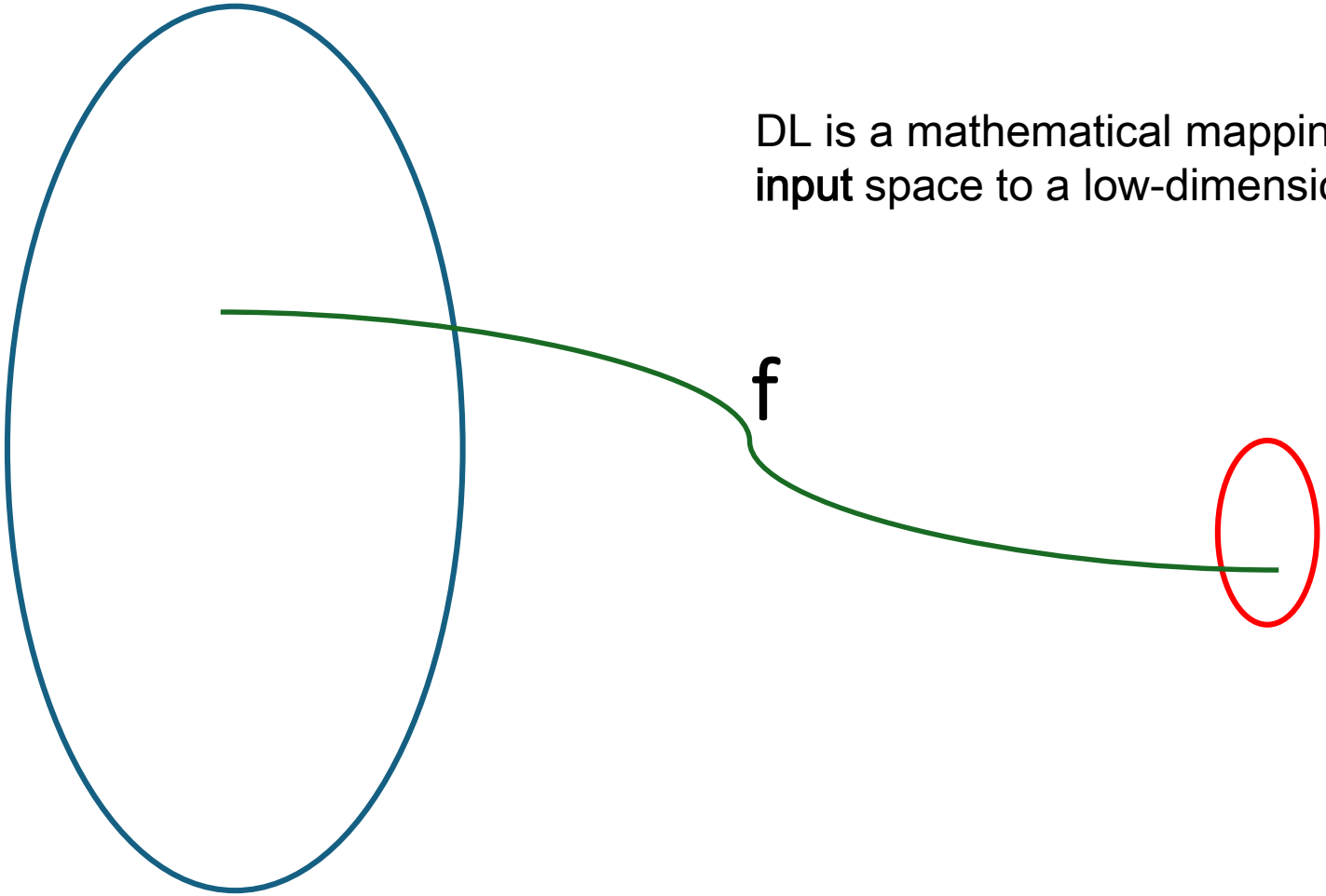
- Custom step-by-step process
- **Many** independent algorithms
- Analysis explicitly **coded by human**
- Works with fewer data

Latest AI Analysis

- End-to-end process
- Fully-automated analysis
- Data **shape** the process
- Error **adapts** the model
- Requires a large amount of data



f(x) = y



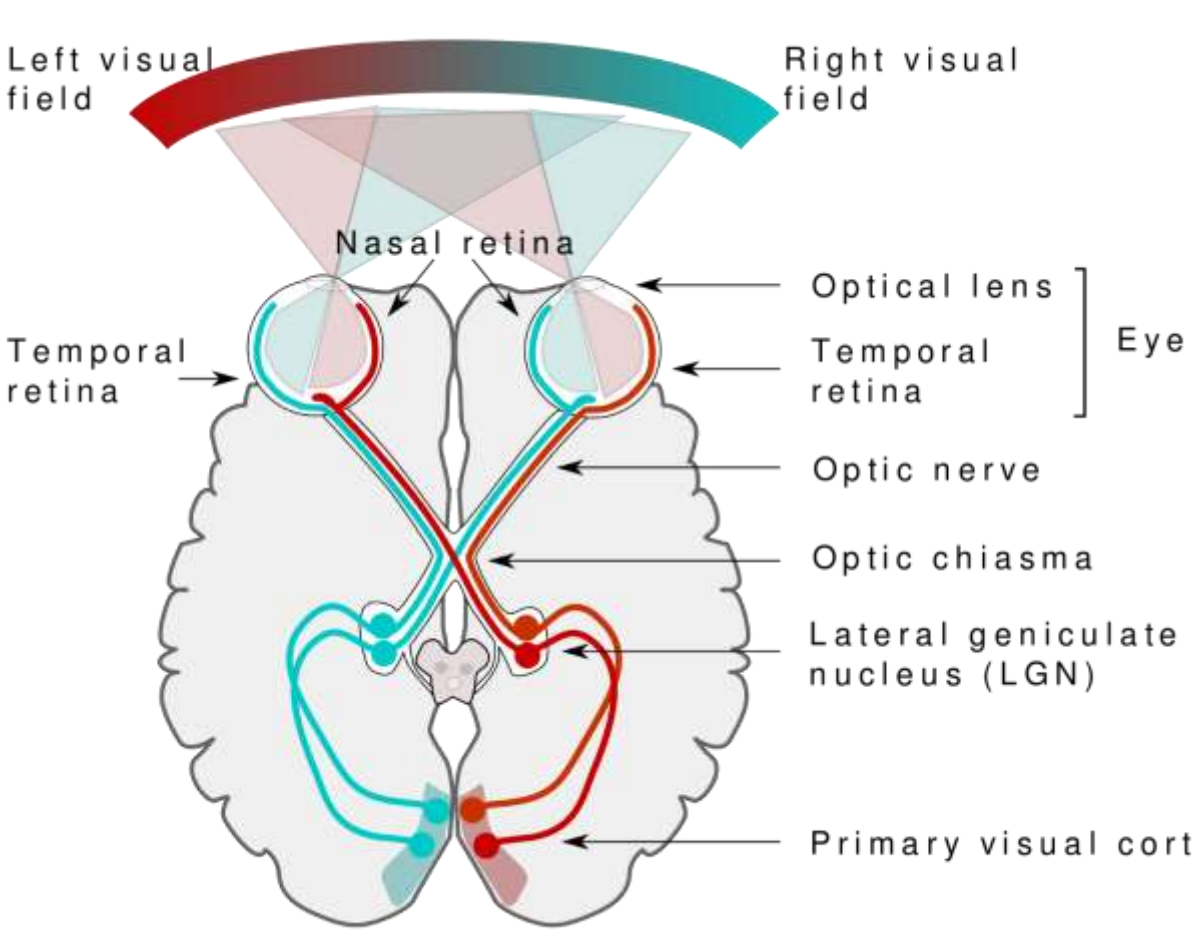
DL is a mathematical mapping from a high-dimensional **input** space to a low-dimensional **semantic output**

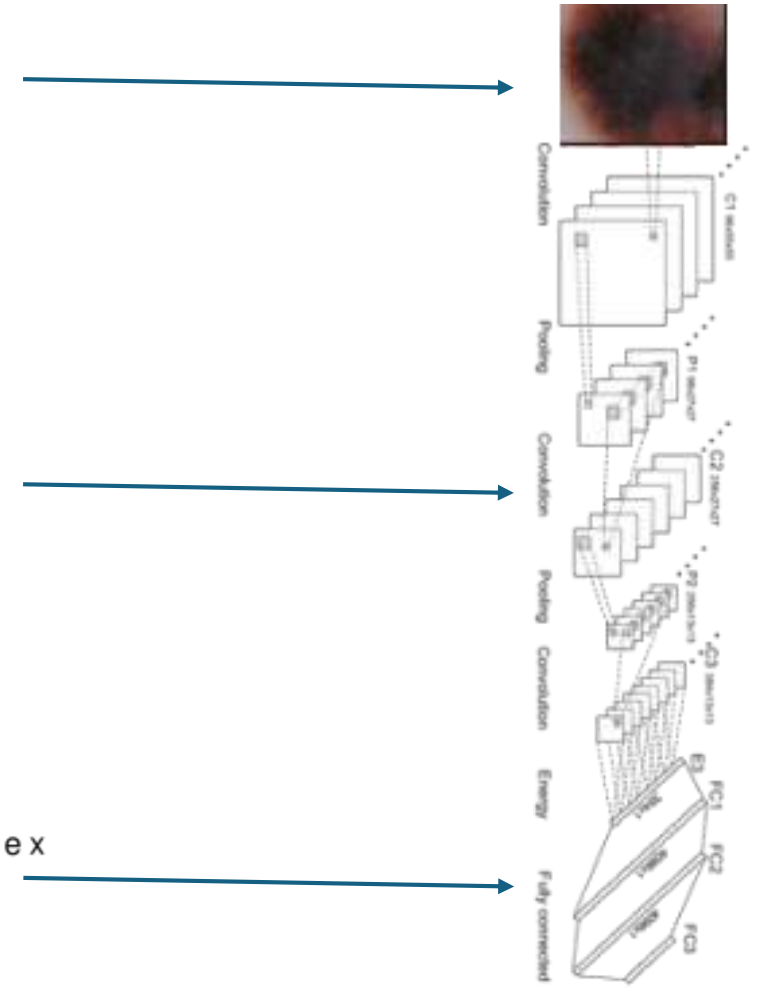
*Oversimplification ;)

Deep into Convolutional Neural Networks

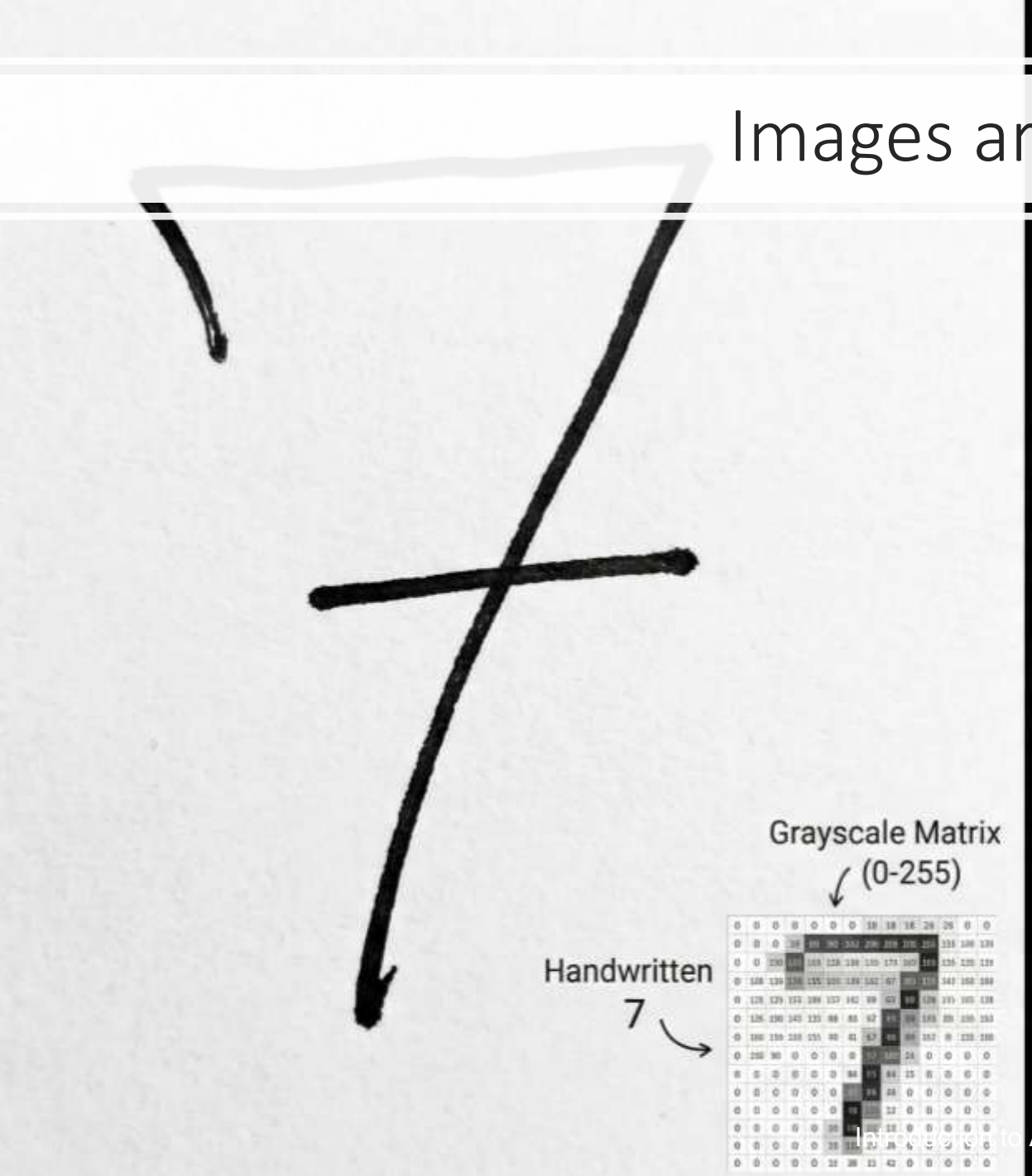
What makes them tick?

Inspiration of Convolutional Neural Networks



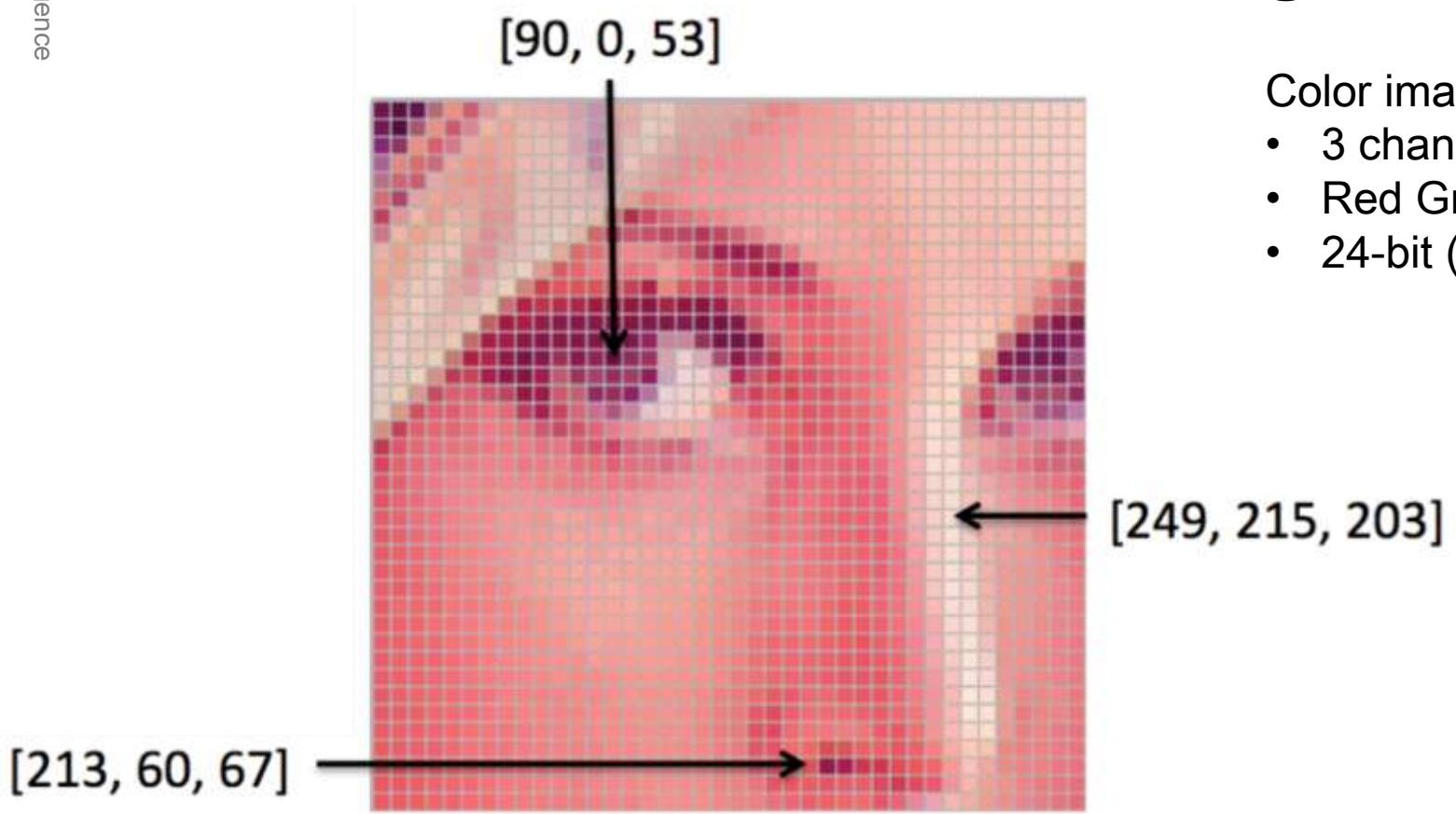


Images are numbers!



0	0	0	0	0	0	0	0	0	28	28	28	0	0
0	0	0	127	127	127	188	182	188	189	207	218	113	122
0	0	127	255	255	255	255	255	255	255	255	255	182	129
0	127	127	142	148	150	161	161	162	163	164	165	203	197
0	128	165	168	170	173	176	167	176	163	171	181	197	198
0	175	171	171	178	176	179	179	178	167	170	184	201	192
0	166	157	167	166	175	184	154	154	175	138	188	197	201
0	154	130	157	164	153	161	136	145	128	137	201	202	201
0	111	113	118	107	82	107	147	154	136	133	202	0	0
0	21	11	0	0	71	92	134	160	130	32	31	0	0
0	10	0	0	0	60	104	123	156	114	31	0	0	0
0	0	0	0	0	73	88	175	144	99	14	0	0	0
0	0	0	0	6	97	122	148	165	78	0	0	0	0
0	0	0	0	62	110	159	167	109	86	0	0	0	0
0	0	0	1	105	182	247	200	223	100	0	0	0	0
0	0	0	4	183	167	178	174	172	131	0	0	0	0

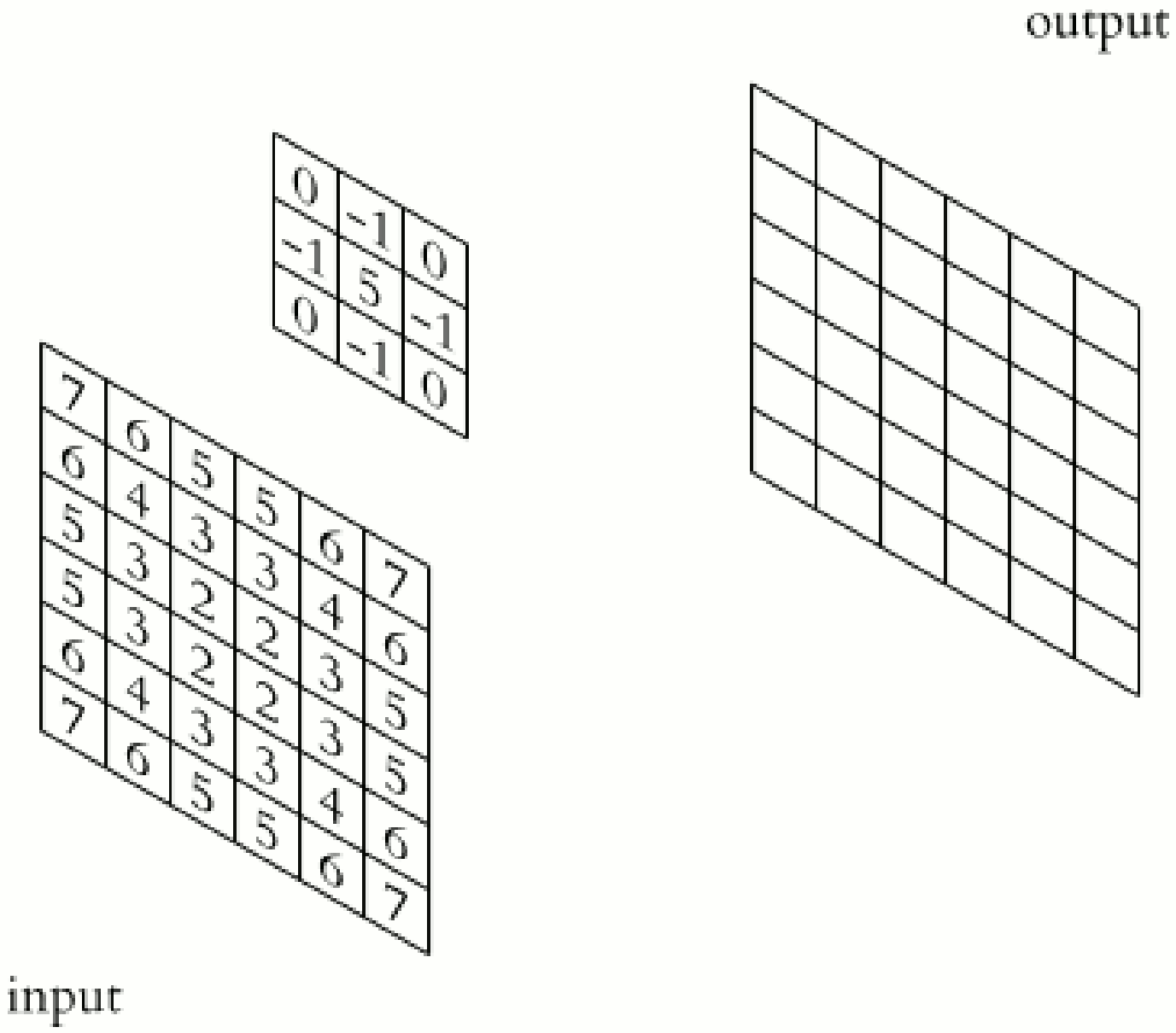
Images are numbers!



Color images

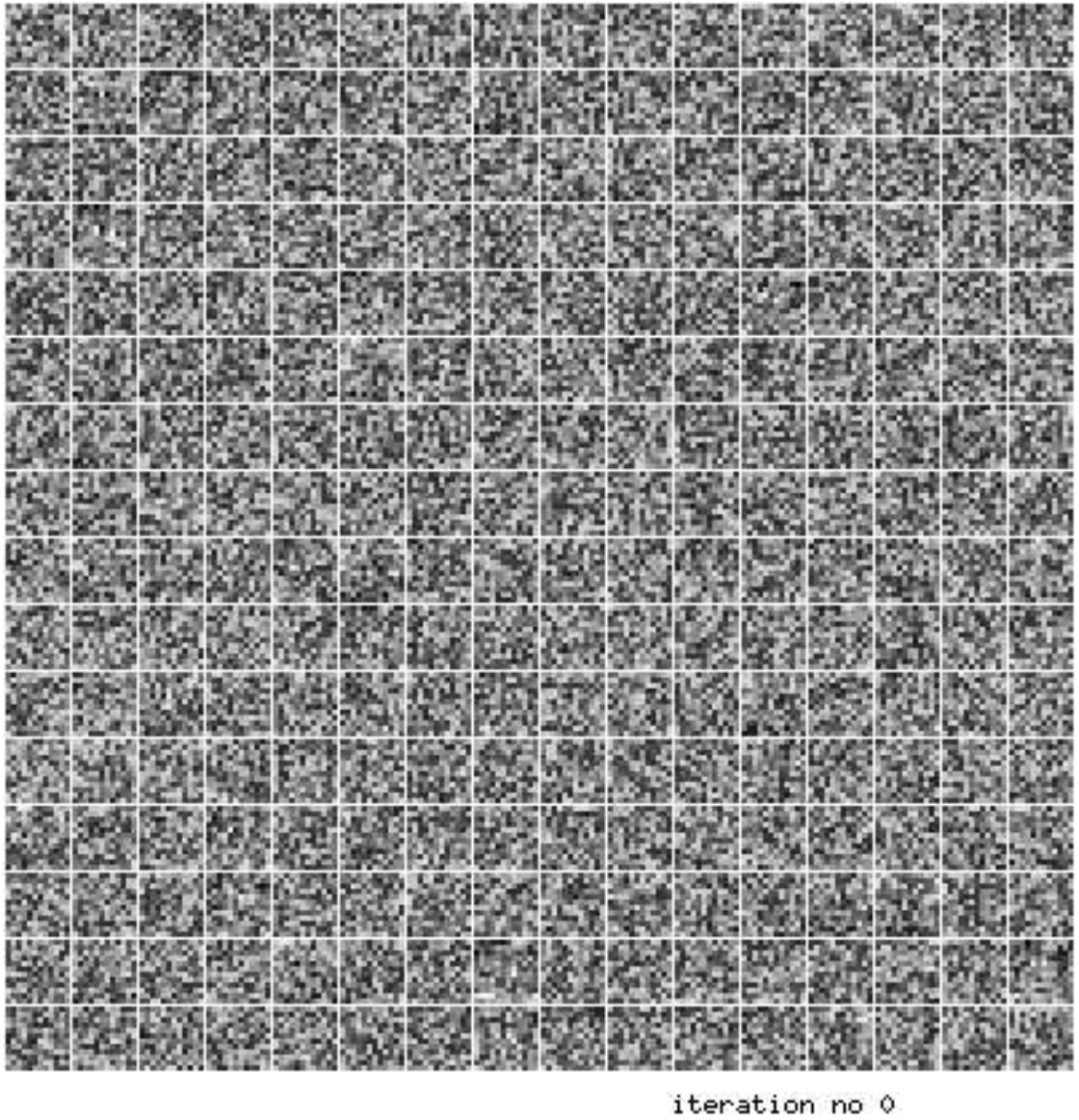
- 3 channels
- Red Green Blue (RGB)
- 24-bit (3x8-bit)

Convolution!

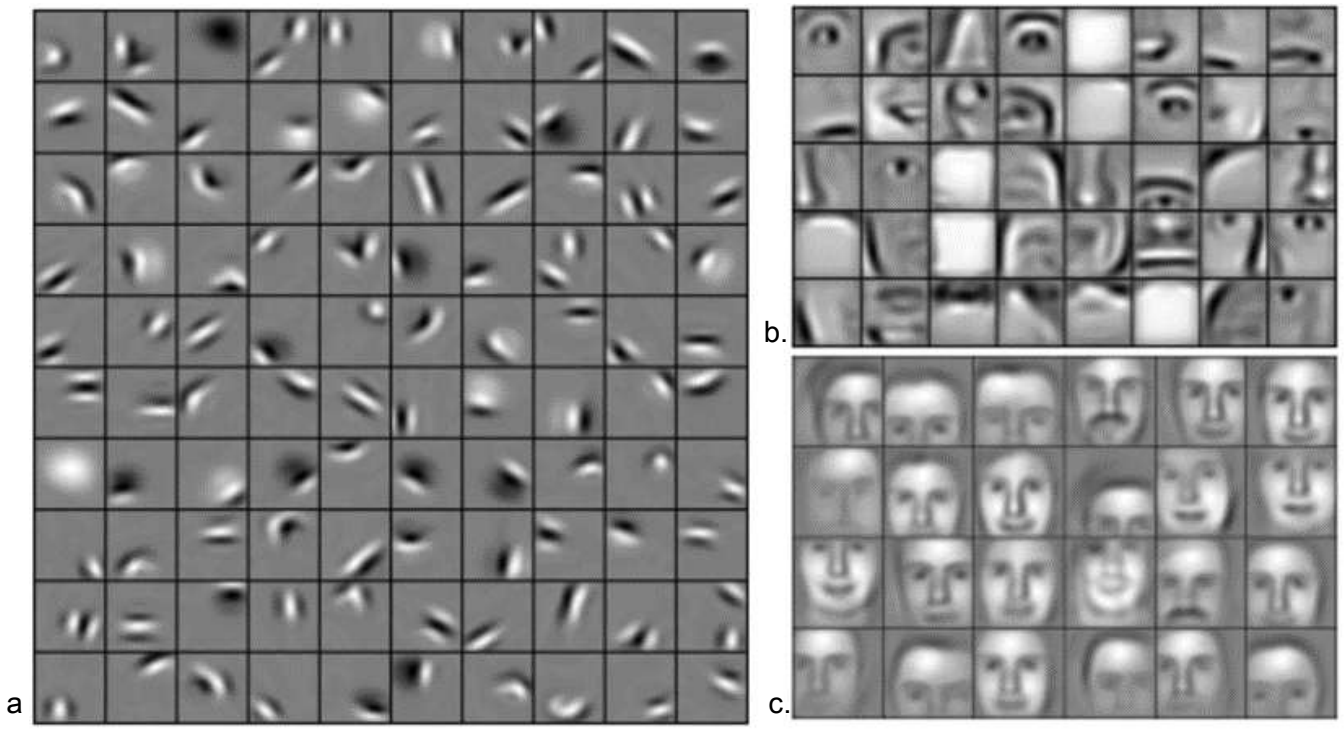


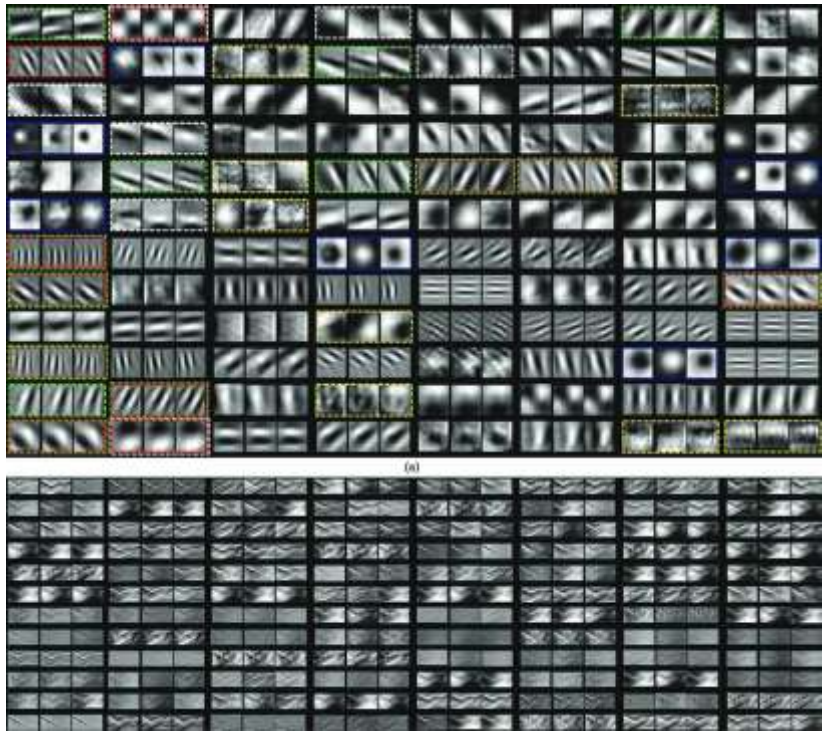
Learnable Filters: From He init to detectors!

Filters



Custom filters!

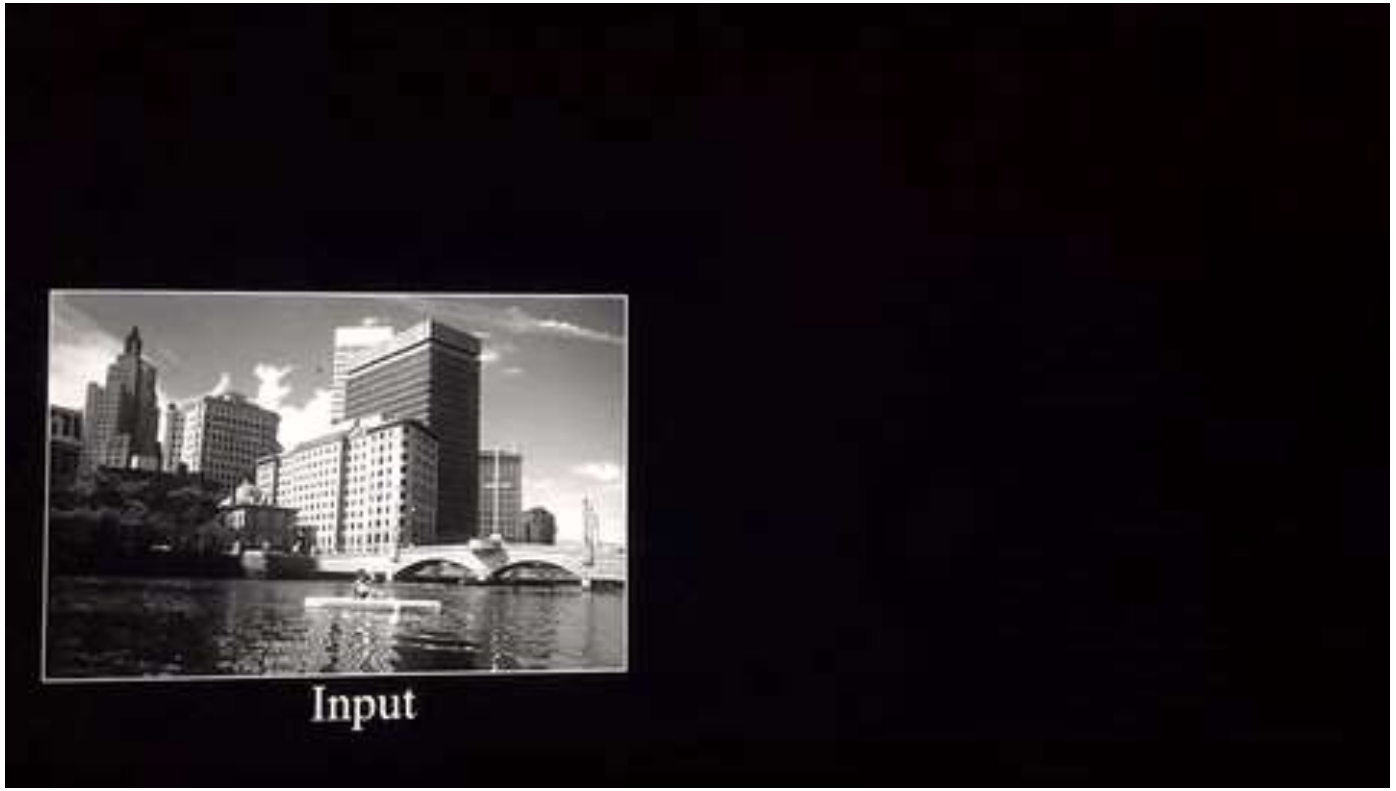




- Lee, H., Grosse, R., Ranganath, R., & Ng, A. Y. (2009, June). Convolutional deep belief networks for scalable unsupervised learning of hierarchical representations. In *Proceedings of the 26th annual international conference on machine learning* (pp. 609-616).

Learnable Filters in Convolutional Layers **(early to deep layers)**

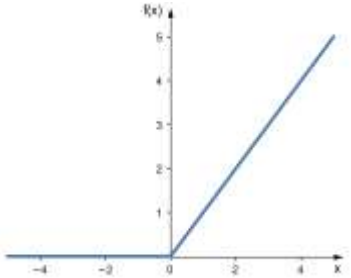
a. **Primitive Gabor-like filters** identifying basic **edges**, **orientations**, and simple **gradients**
b. **Part-based detectors** combining edges into textures and **local structures**
c. **High-level concept filters** integrating complex, class-specific **semantic representations**



Appling Learnable Features to Input Images

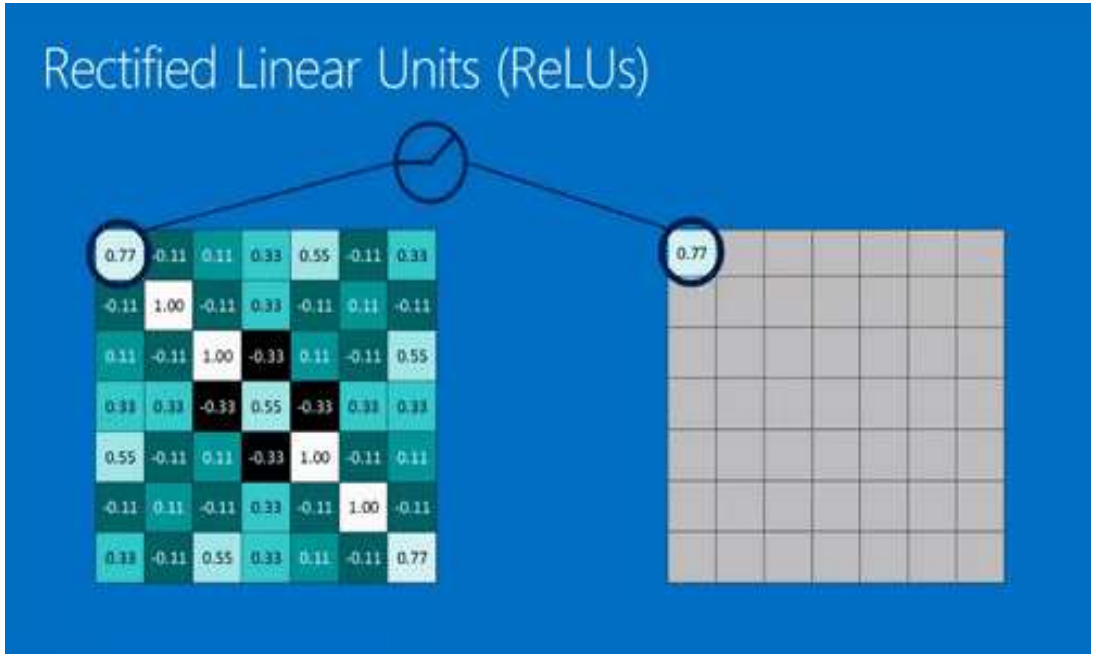
Feature Maps

Sparsity as an Accelerant of Generalization

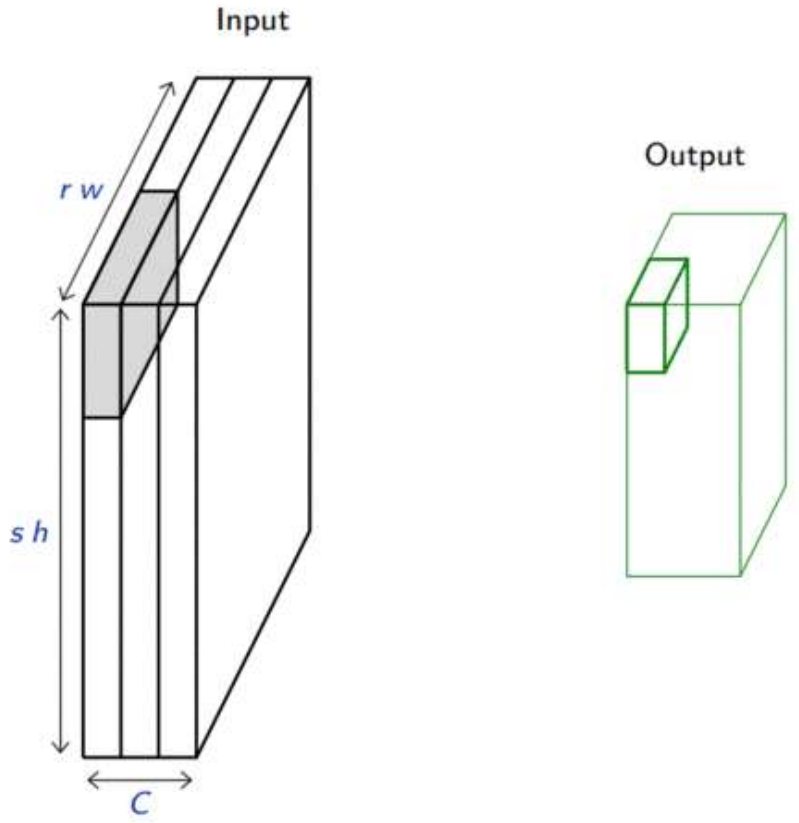


Activation Function

- Non-linearity to remove negative neurons [f(x)=max(0,x)] while allowing positive signals to pass unchanged
- Mitigates the vanishing gradient problem



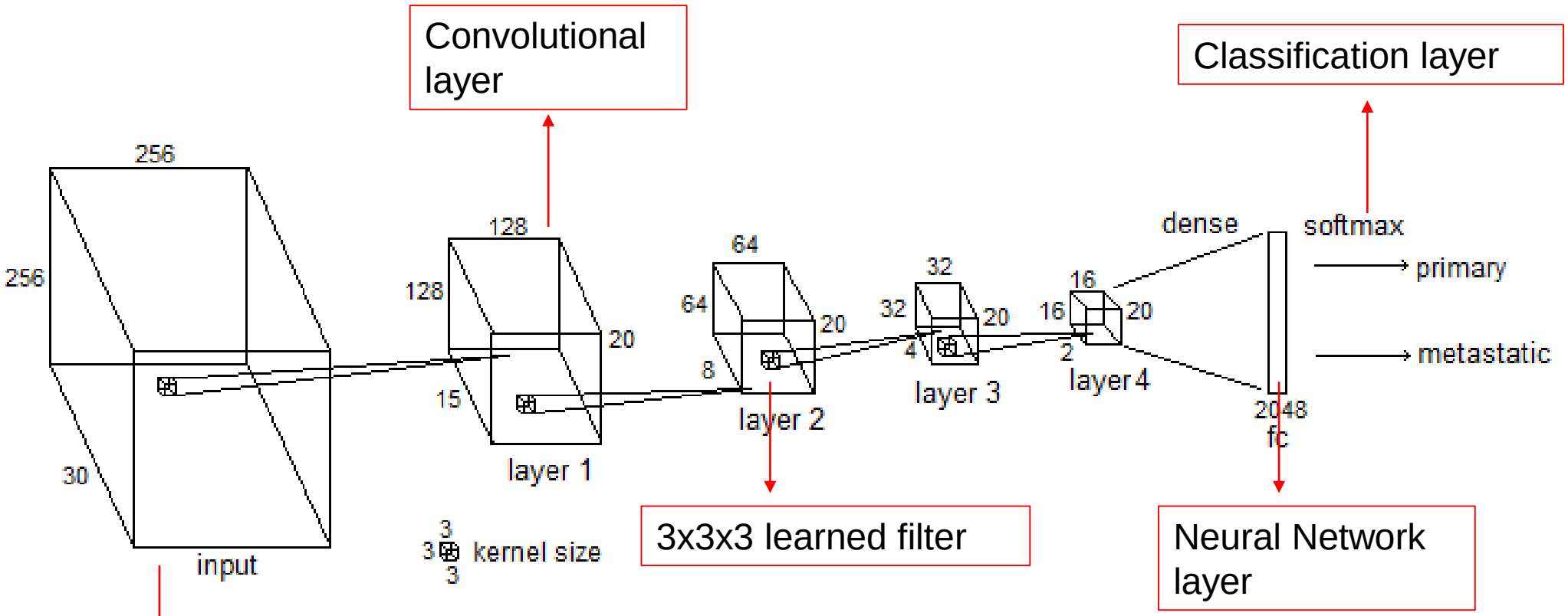
Dimensionality Reduction – Feature Distillation



Pooling layer

- Down-samples the **feature maps**
- Prevents the **memorization** of the dataset
- **Reduces** the parameters of the model

A TYPICAL CNN



Trivizakis, E., Manikis, G. C., Nikiforaki, K., Drevelegas, K., Constantinides, M., Drevelegas, A., & Marias, K. (2018). Extending 2-D convolutional neural networks to 3-D for advancing deep learning cancer classification with application to MRI liver tumor differentiation. *IEEE journal of biomedical and health informatics*, *23*(3), 923-930.