

AI from Scratch: Let's Build and Train a Perceptron in Pure Swift

Johannes Fahrenkrug - @jfahrenkrug - springenwerk.com - #PragmaConf 2025



HISTORY!

MATH!

CODE!

INTRIGUE!

INTEGER!



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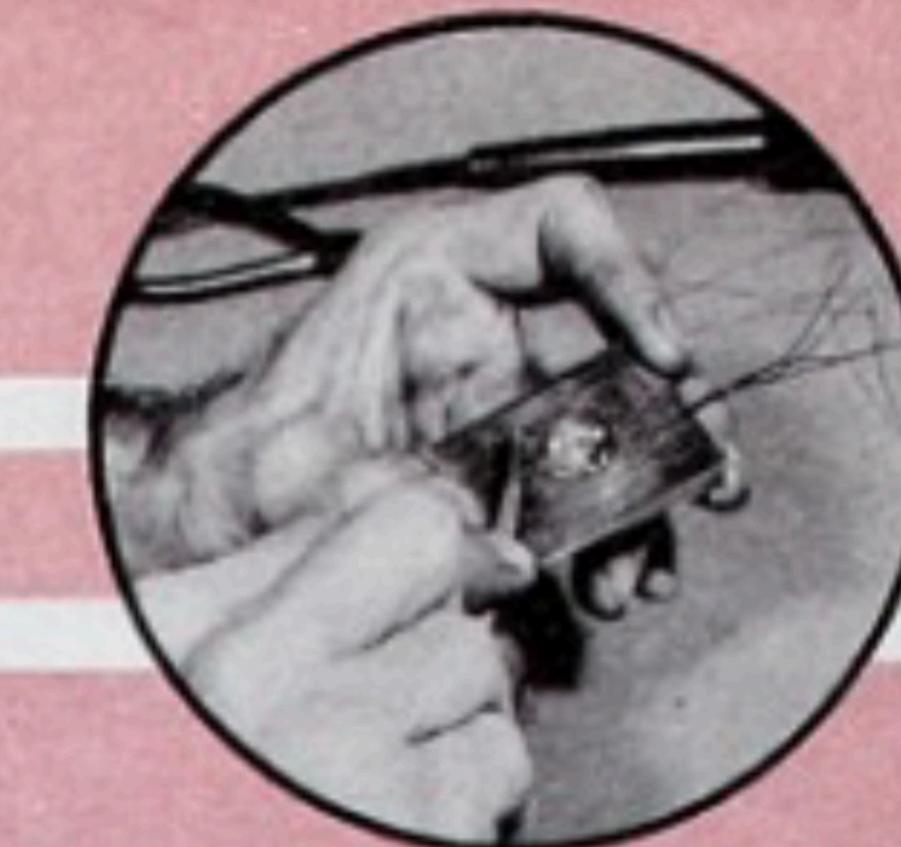
Perceptron



Vol. VI, No. 2, Summer 1958

research trends

CORNELL AERONAUTICAL LABORATORY, INC., BUFFALO 21, NEW YORK



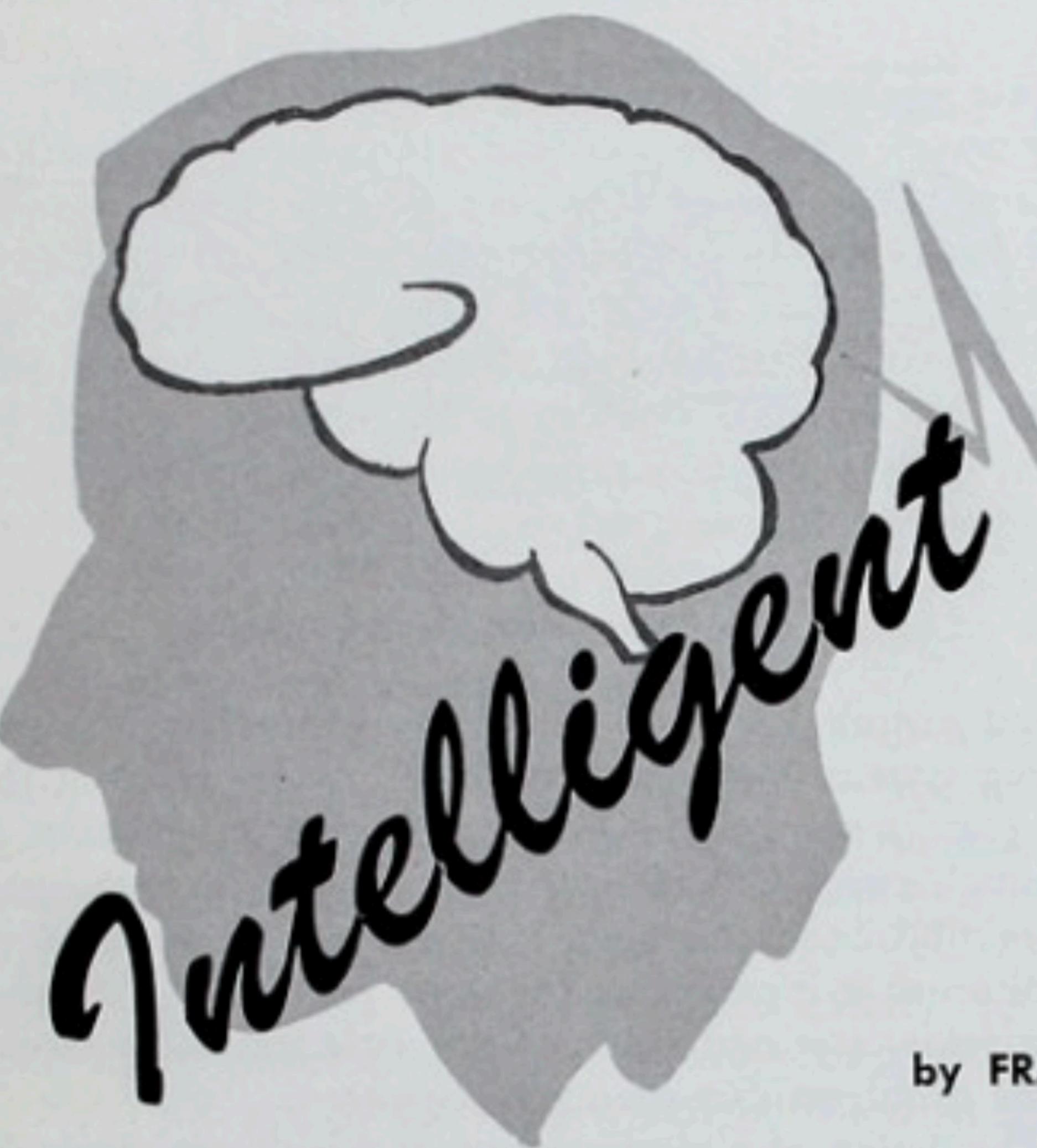
The Design of an



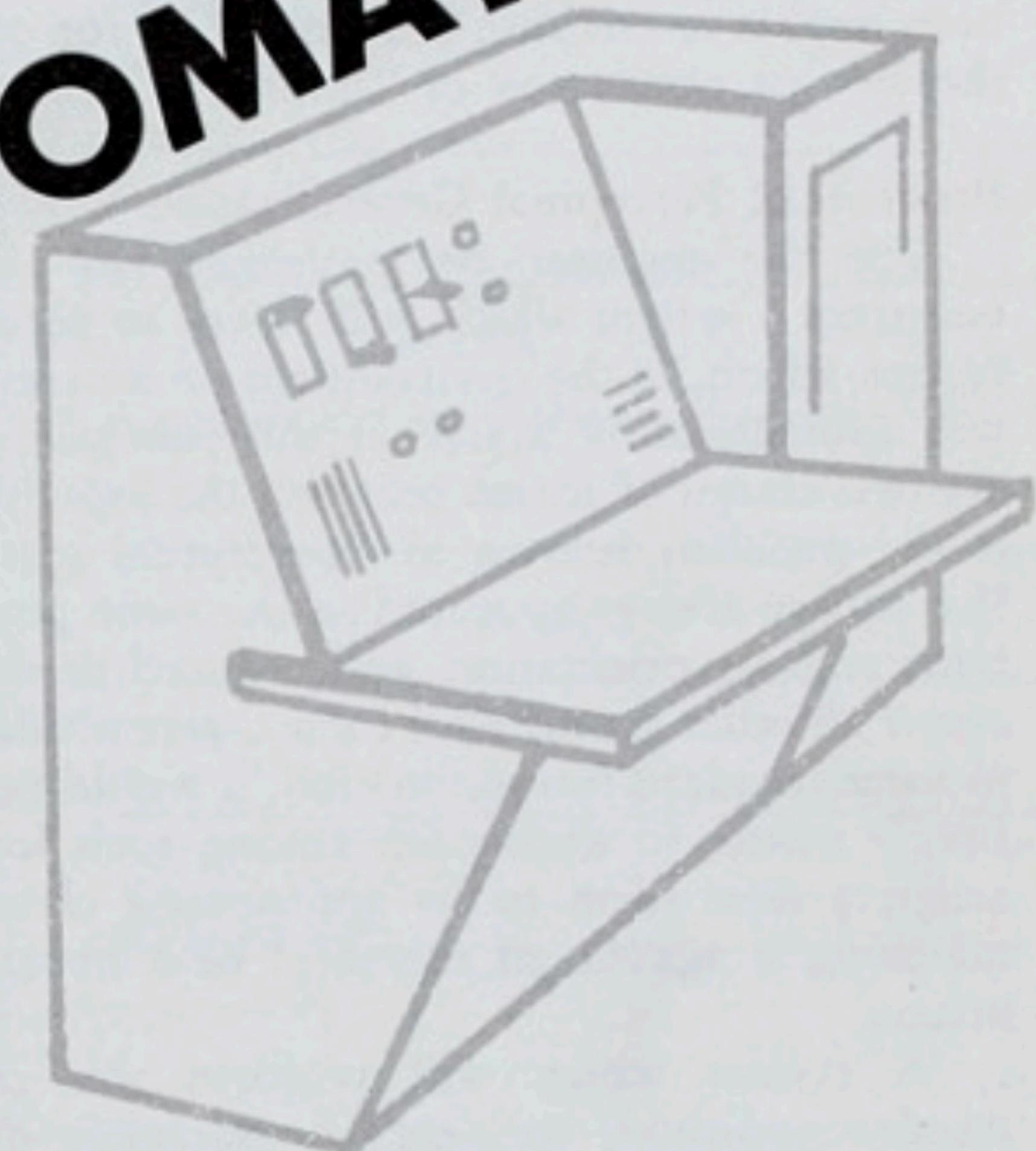
AUTOMATON



The Design of an

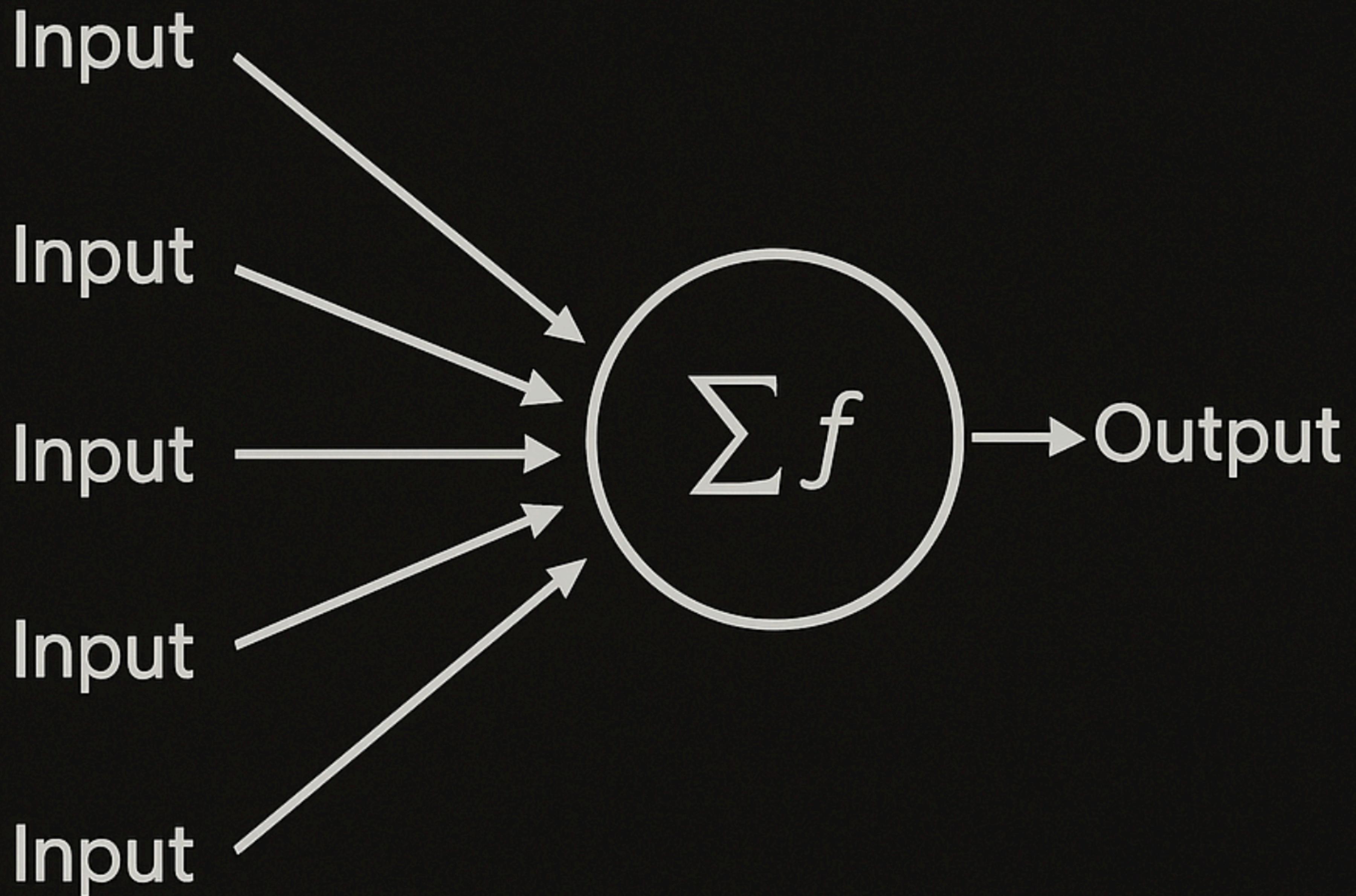


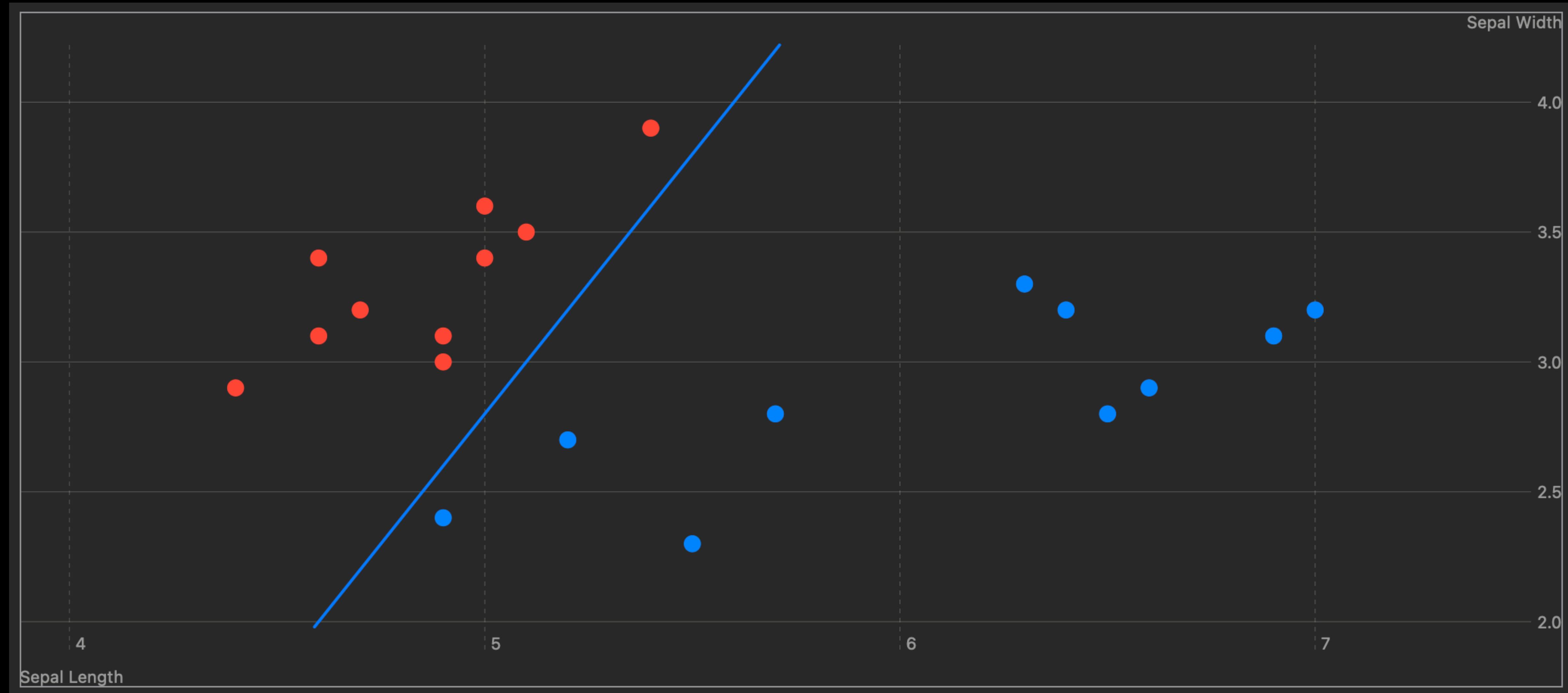
AUTOMATON

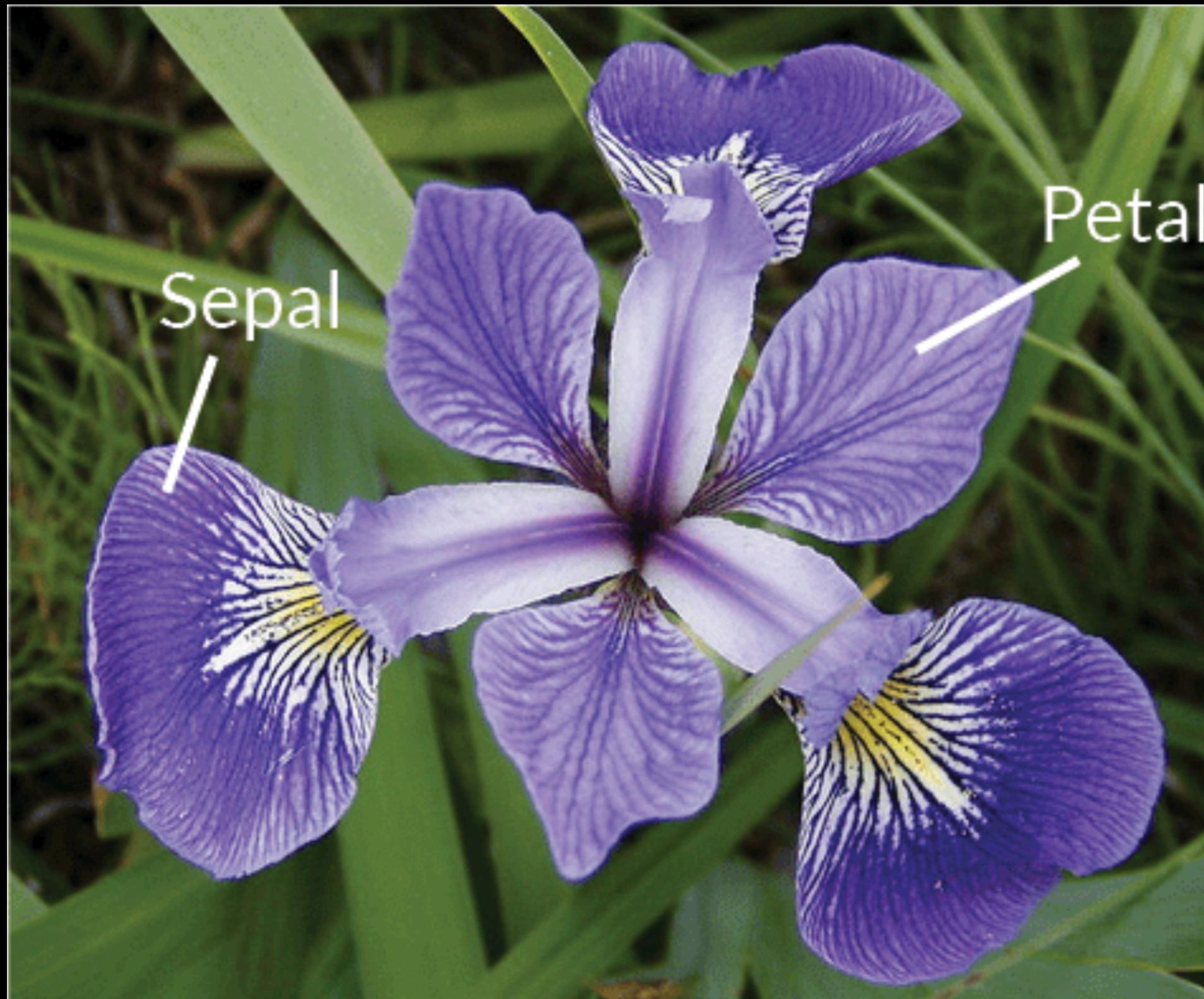


by FRANK ROSENBLATT

Introducing the perceptron — A machine which senses,
recognizes, remembers, and responds like the human mind.



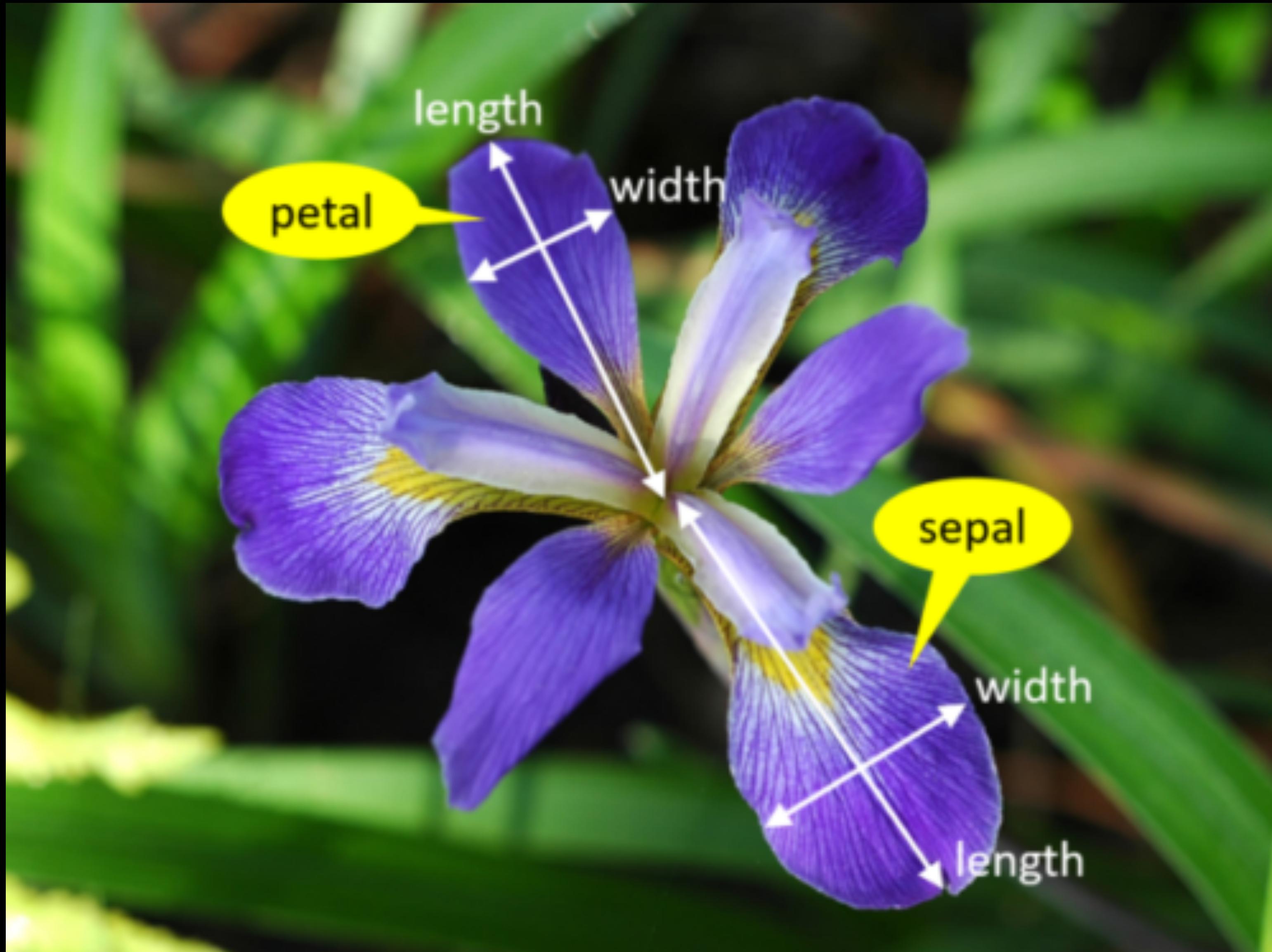




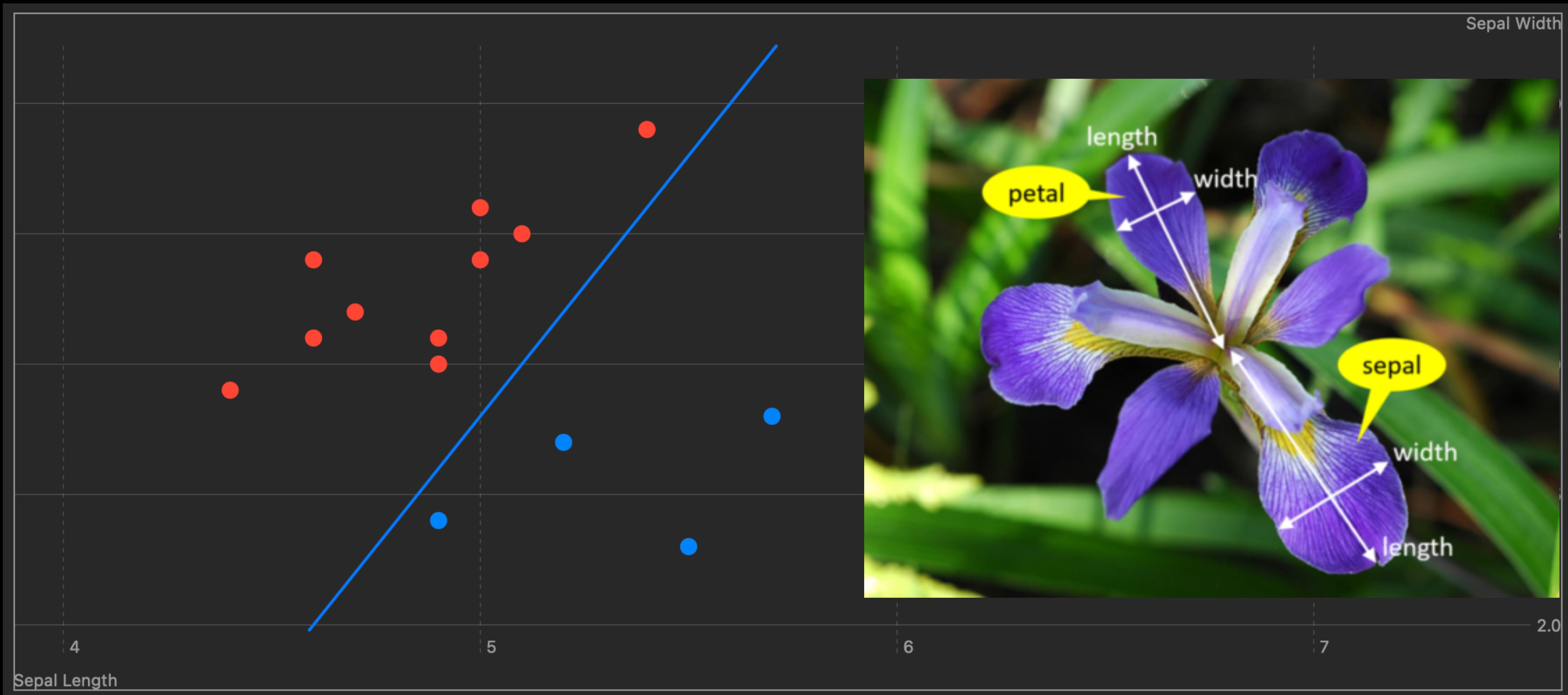
Iris Versicolor



Iris Setosa

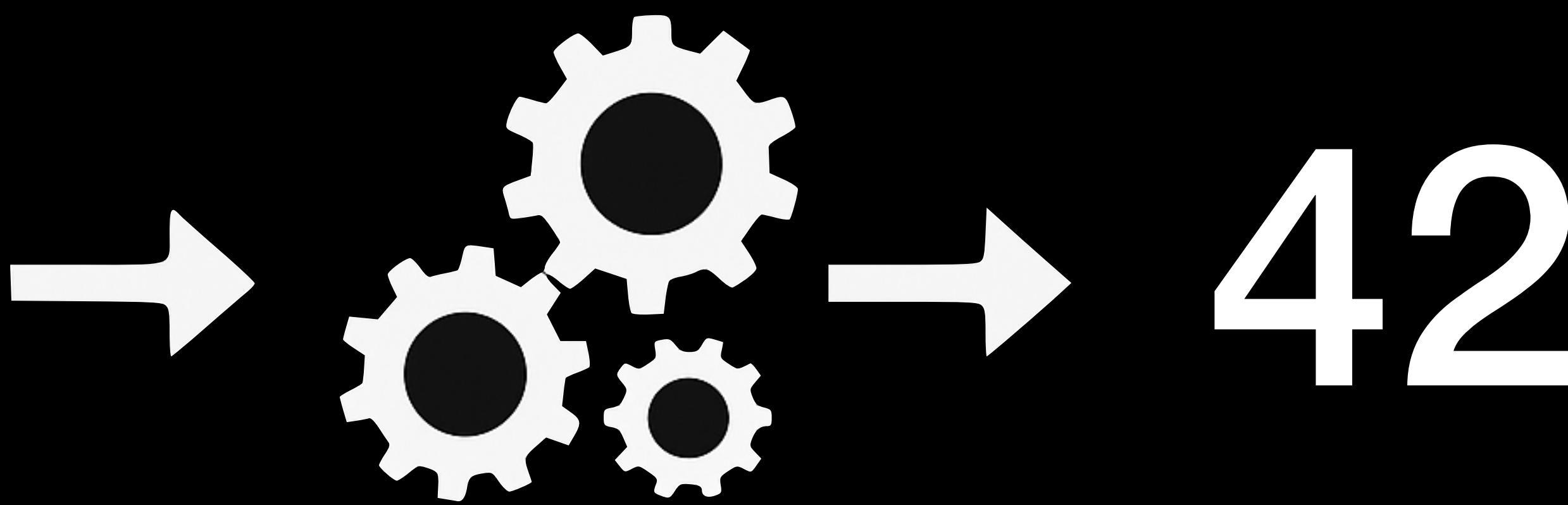


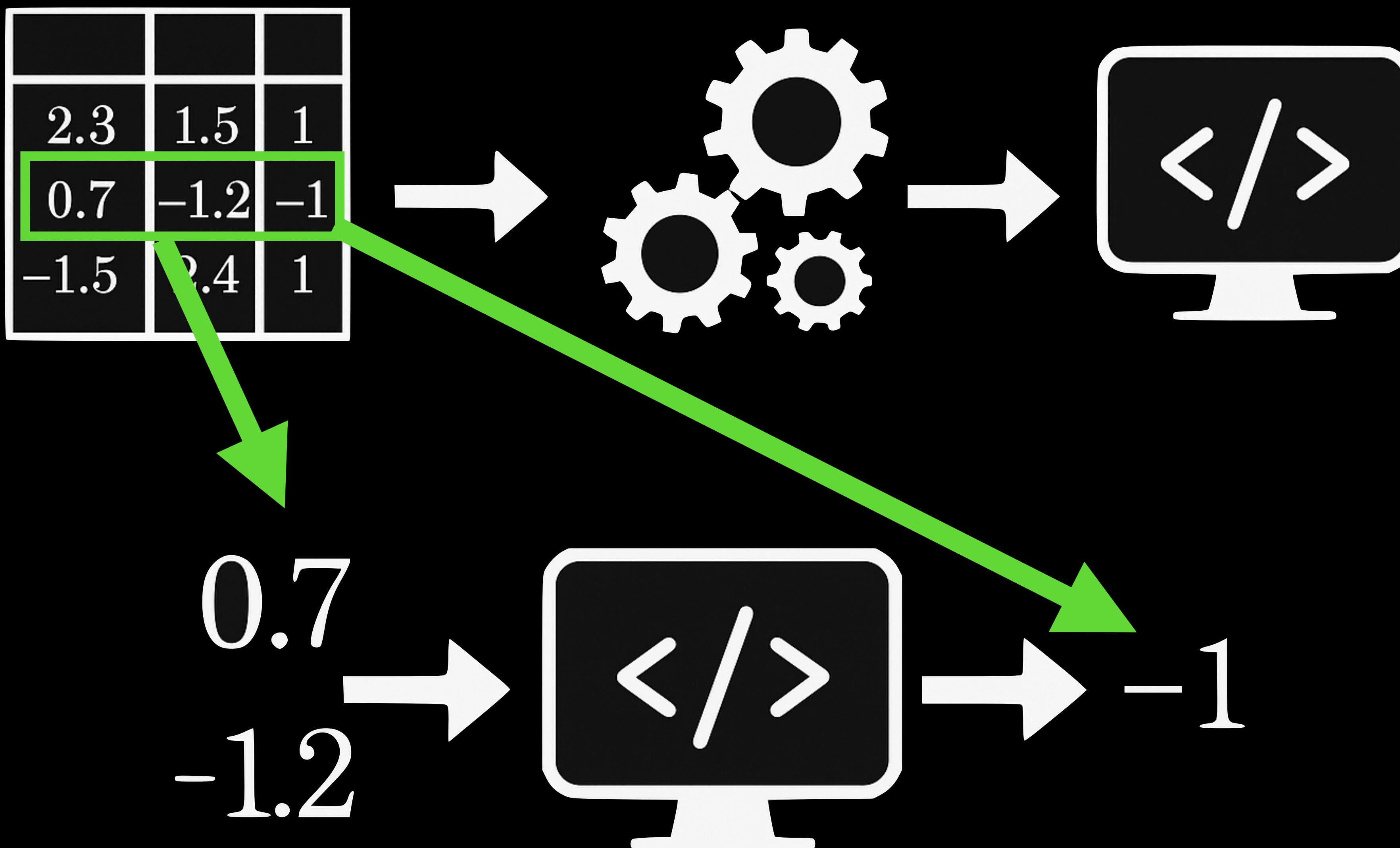
<https://www.kaggle.com/code/doreamon11122000/iris-flower-dataset-eda>



| Age | M/F | Weight | Length of Stay | Re-admitted? |
|-----|-------|--------|----------------|--------------|
| 71 | 2 (M) | 139 | 10 | YES |
| 21 | 1 (F) | 68 | 1 | NO |
| 45 | 2 (M) | 95 | 15 | YES |
| 69 | 1 (F) | 110 | 8 | YES |

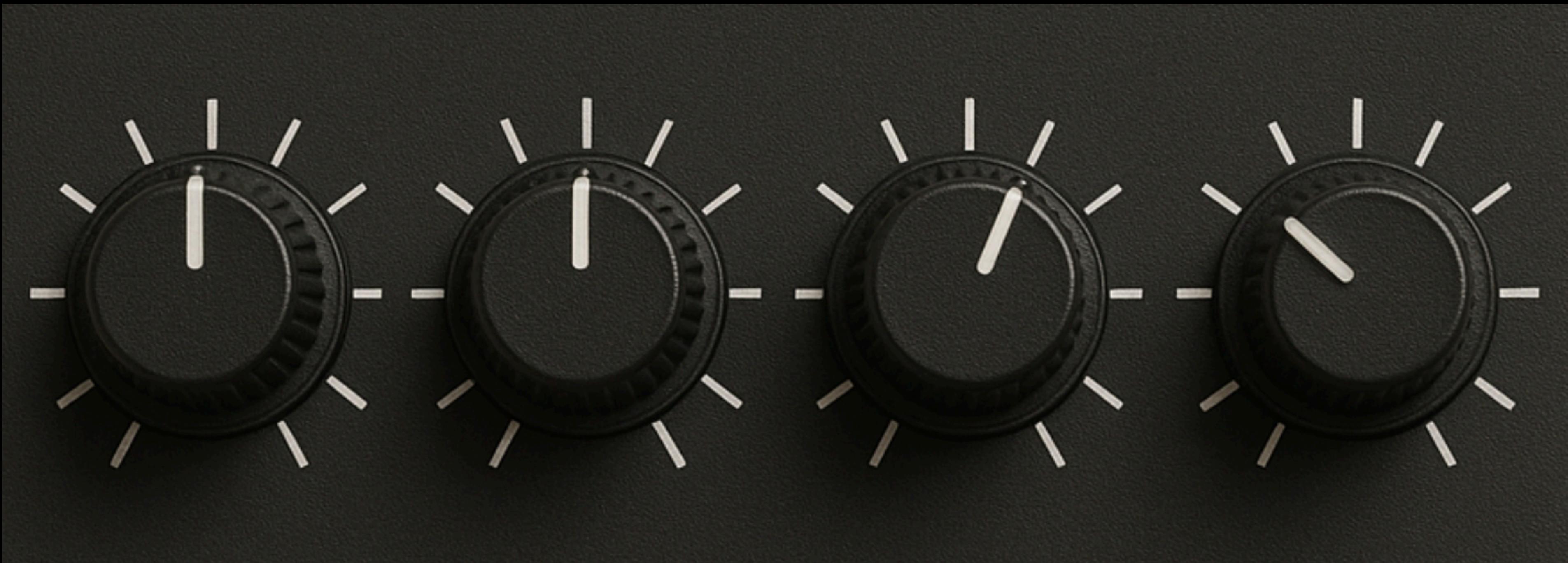
| | | |
|------|------|----|
| | | |
| 2.3 | 1.5 | 1 |
| 0.7 | -1.2 | -1 |
| -1.5 | 2.4 | 1 |





Weights & Bias





1. Dot Product

$$\begin{matrix} x_1 * w_1 \\ + \\ x_2 * w_2 \end{matrix}$$

$$\begin{matrix} 0.7 * 2.4 \\ + \\ -1.2 * 0.5 \\ = \\ 1.08 \end{matrix}$$

2. Bias

$$\begin{matrix} \text{dot product result} >= 0 \\ + \\ \text{bias} \end{matrix}$$

$$\begin{matrix} 1.08 \\ + \\ -1.8 \\ = \\ -0.72 \end{matrix}$$

3. Activation

$$\begin{matrix} ? 1 : -1 \end{matrix}$$

$$\begin{matrix} -0.72 >= 0 \\ ? 1 : -1 \\ = \\ \boxed{-1} \end{matrix}$$

Demo 1

Training



Training



| Training Data | | | |
|---------------|--------|--------|-------|
| # | Input1 | Input2 | Label |
| 1 | 0.0 | 0.0 | -1 |
| 2 | 0.0 | 1.0 | -1 |
| 3 | 1.0 | 0.0 | -1 |
| 4 | 1.0 | 1.0 | 1 |

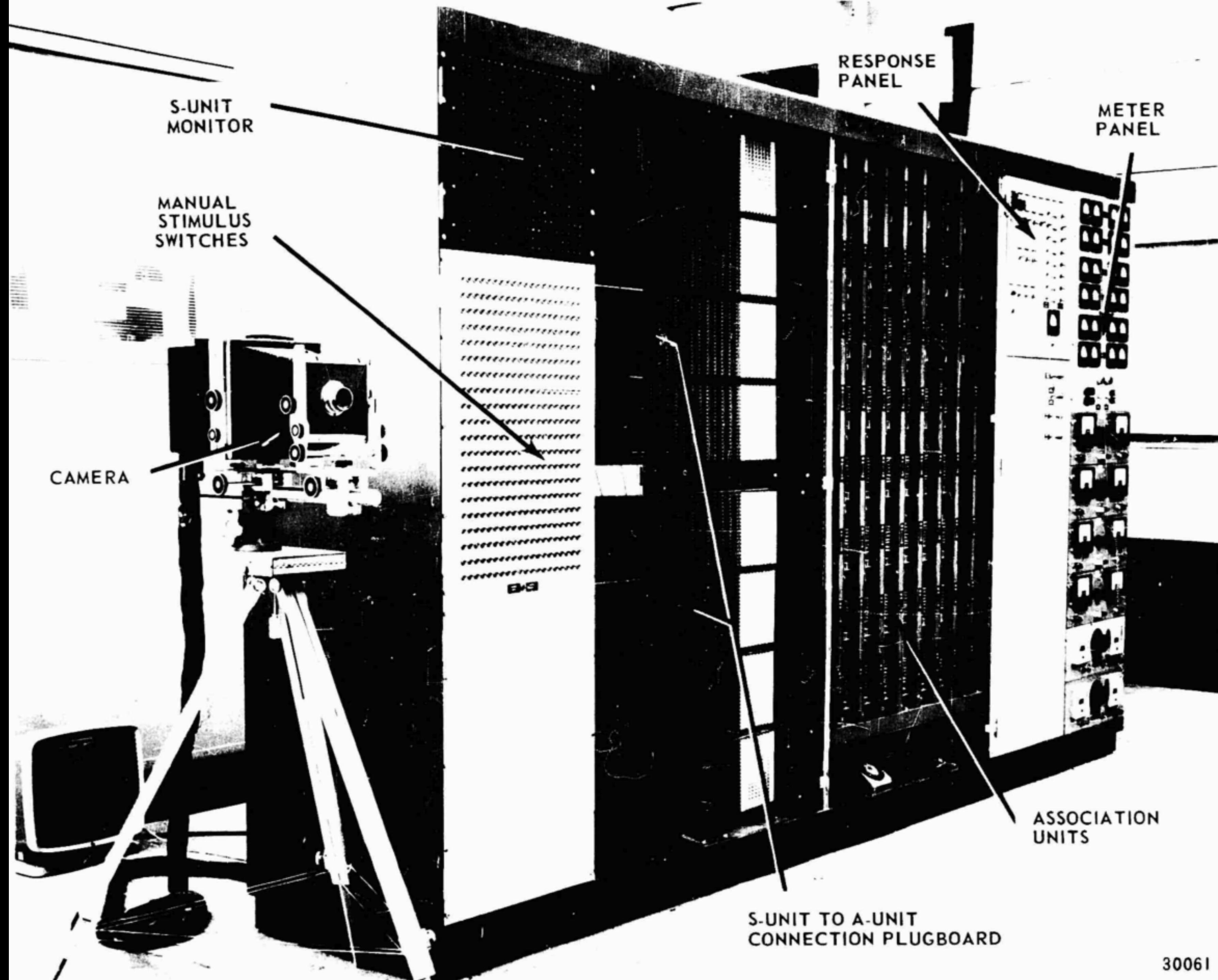
1. Set a “learning rate”, say **0.2**
2. Set a max number of “epochs”
3. Set weights to random values
4. Iterate over the training data
5. Make a prediction, say **-1**
6. Calculate error: expected **(1)** - predicted **(-1)** = **2**
7. Update all weights (and bias):
$$\text{newW1} = \text{oldW1} + (\text{error} * \text{rate} * \text{input1})$$
$$\text{newW1} = 0.5 + (2 * 0.2 * 1.0)$$
$$= 0.9$$
8. Continue

Tiny nudges to reduce the errors

Demo 2

HISTORY!

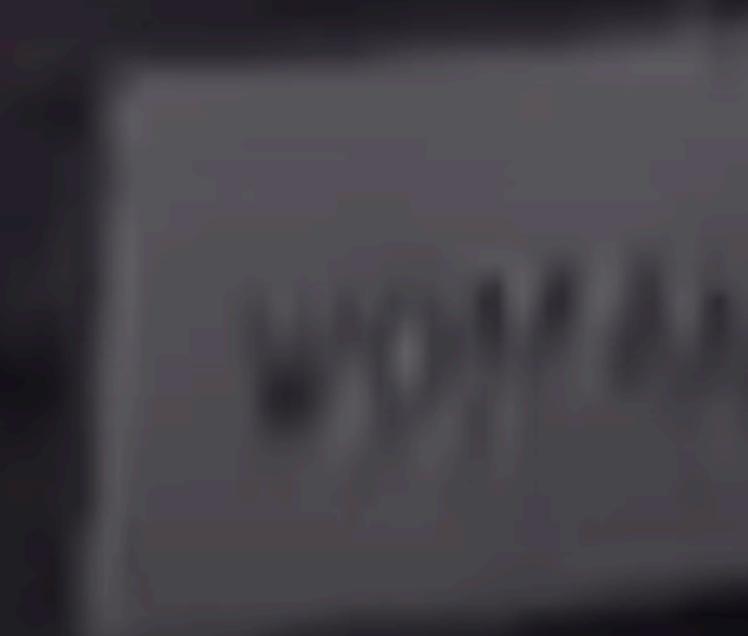
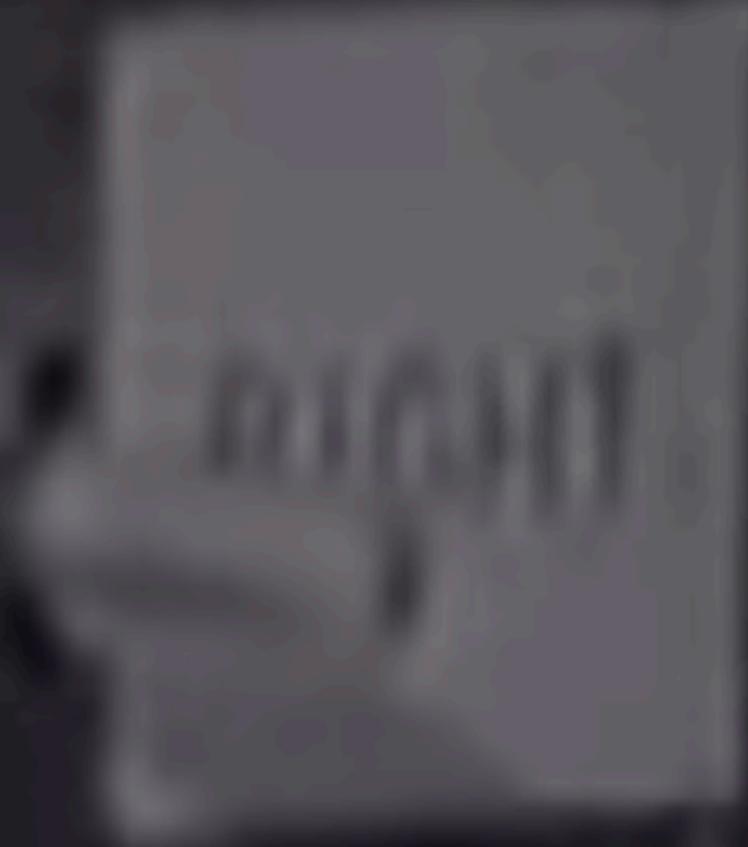
Mark 1 Perceptron















Woman

main

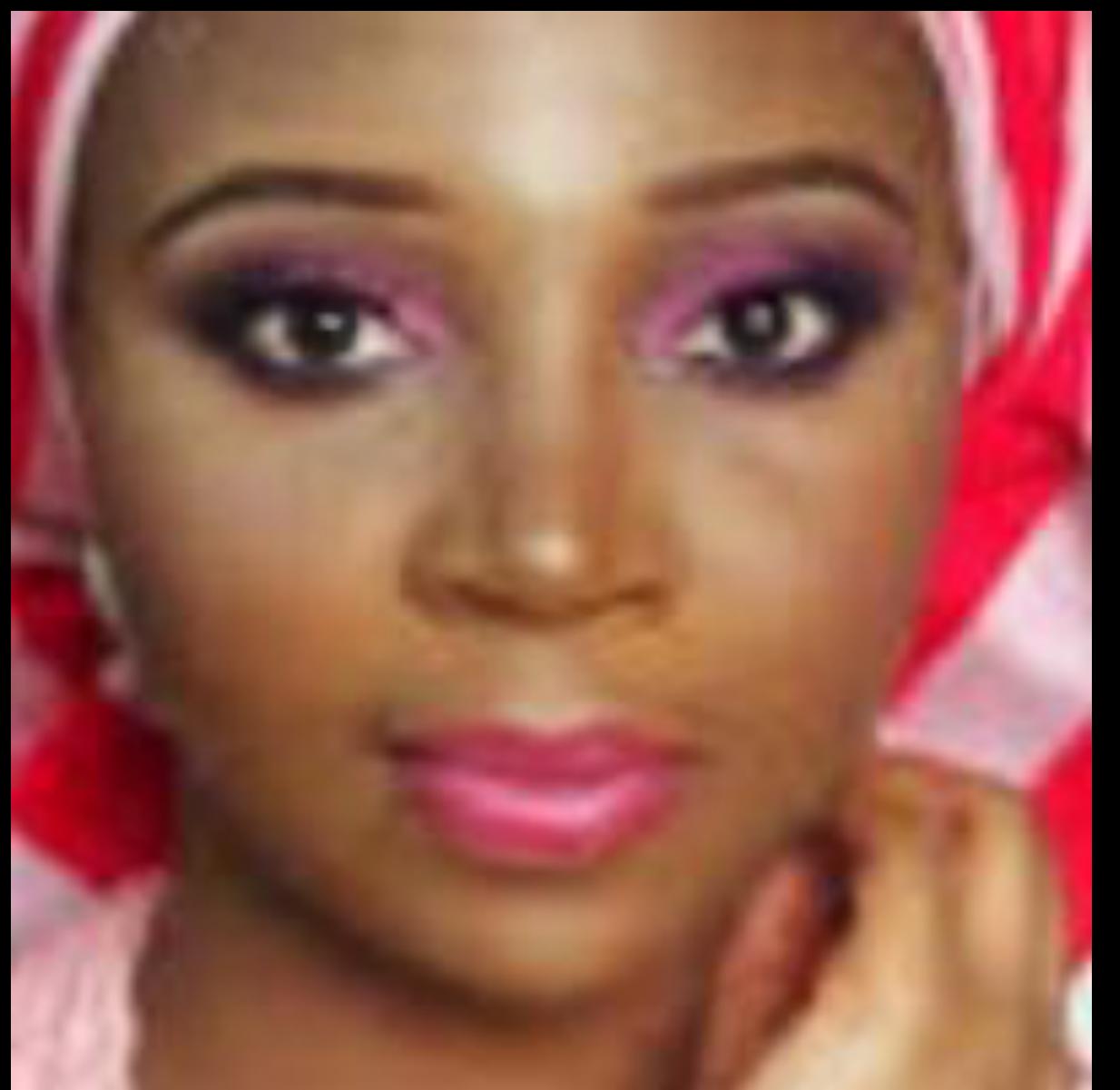
20 x 20

400 inputs

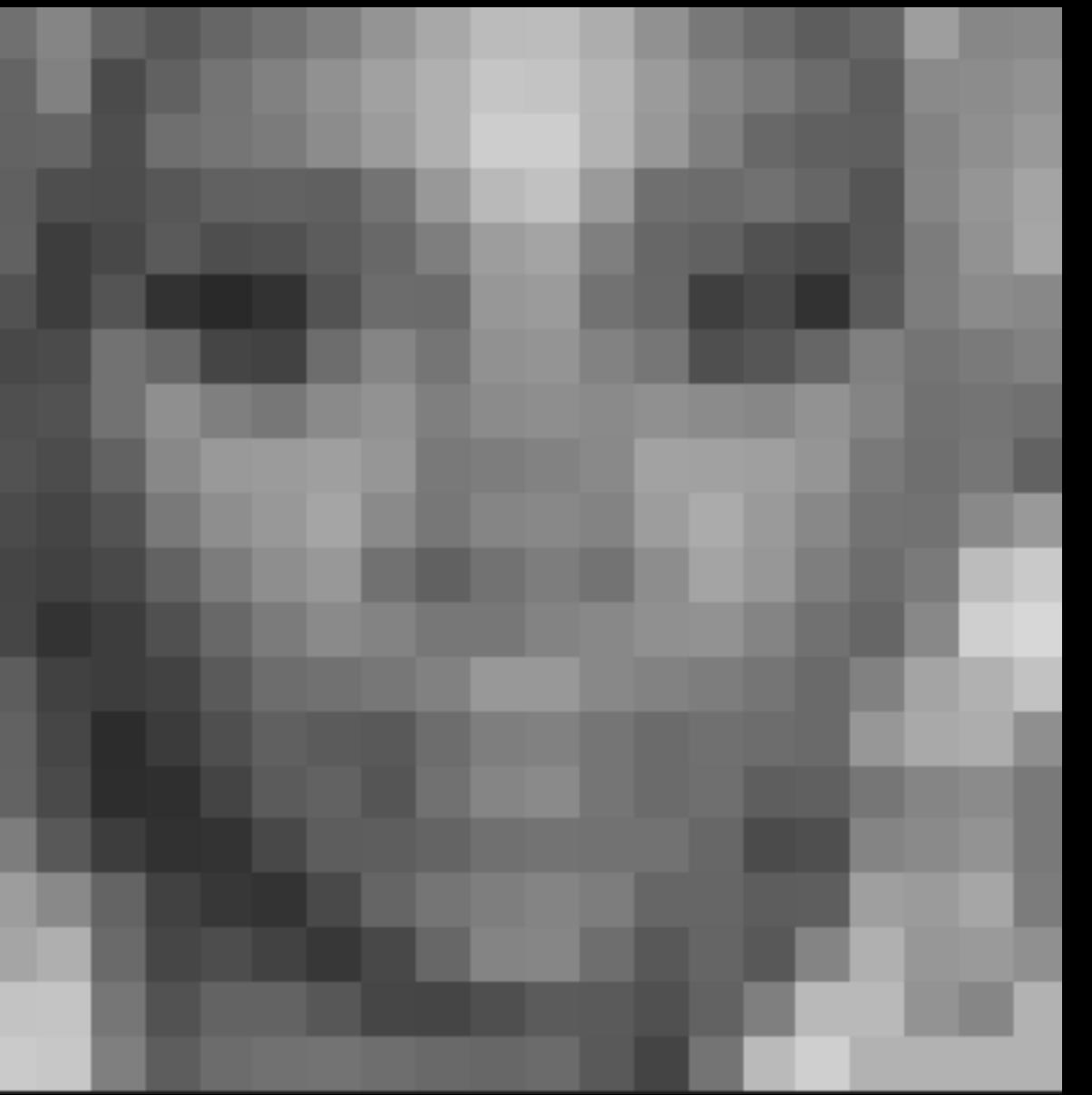
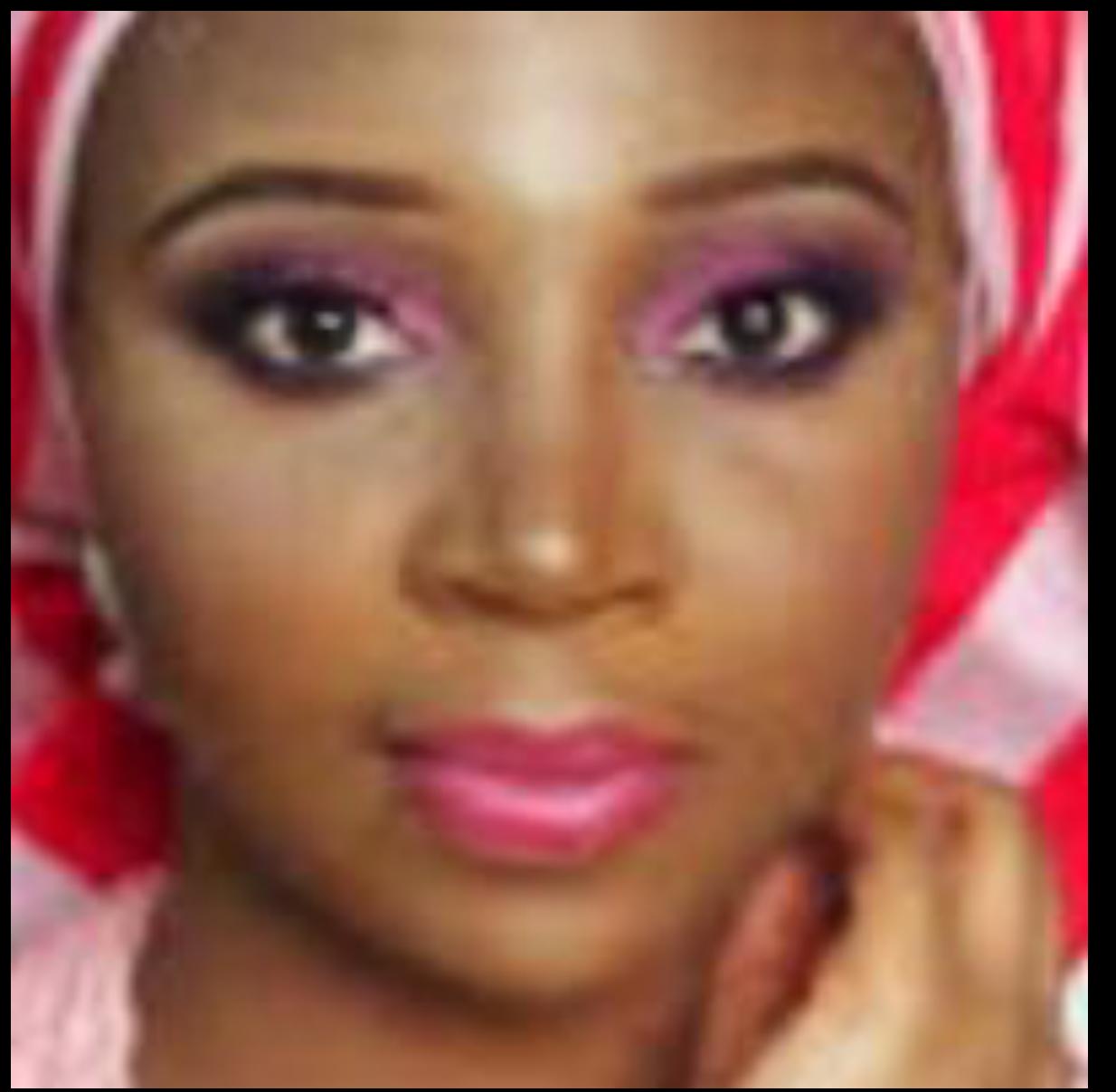
400 weights

Our perceptron can do that!





0.32777036429426293,
0.25392303940330374,
0.078381193699081808,
0.11703406150503087,
0.37321835959935168,
0.25101356379837647,
0.044903381464514378,
0.83435575004113094,
0.3775550942451921,
0.23241184551774982,
0.59401048617336316,
0.047106292622483663,
0.28839735245249742,
0.016745347335530694,
0.2544021108941466,
0.21682148093507306,
0.38603014673867891,
0.36351060632153387,
0.038119056445925628,
0.12119960989131495,
0.112935944030299,
0.26711006802577131,
0.13971403023318915,
0.18299742338024191,



0.35787647741669626,
0.62534015343127758,
0.074369857262695155,
0.20754403520080994,
0.5421155843788934,
0.24763652015655535,
0.4602652599915209,
0.051378450396482027,
0.56910838557126653,
0.95486432151799661,
0.57497417695802133,
0.46888967536678122,
0.22032336457796511,
0.048087645862134966,
0.092539468932609628,
0.10713123790158115,
0.14858167765775868,
0.51737786086628912,
0.31379609563381544,
0.033294401465568176,
0.0097289295078757804,
0.61139823668324167,
0.25893043797871801,
0.37422438403079256,
0.015540486338675146,

Training Data

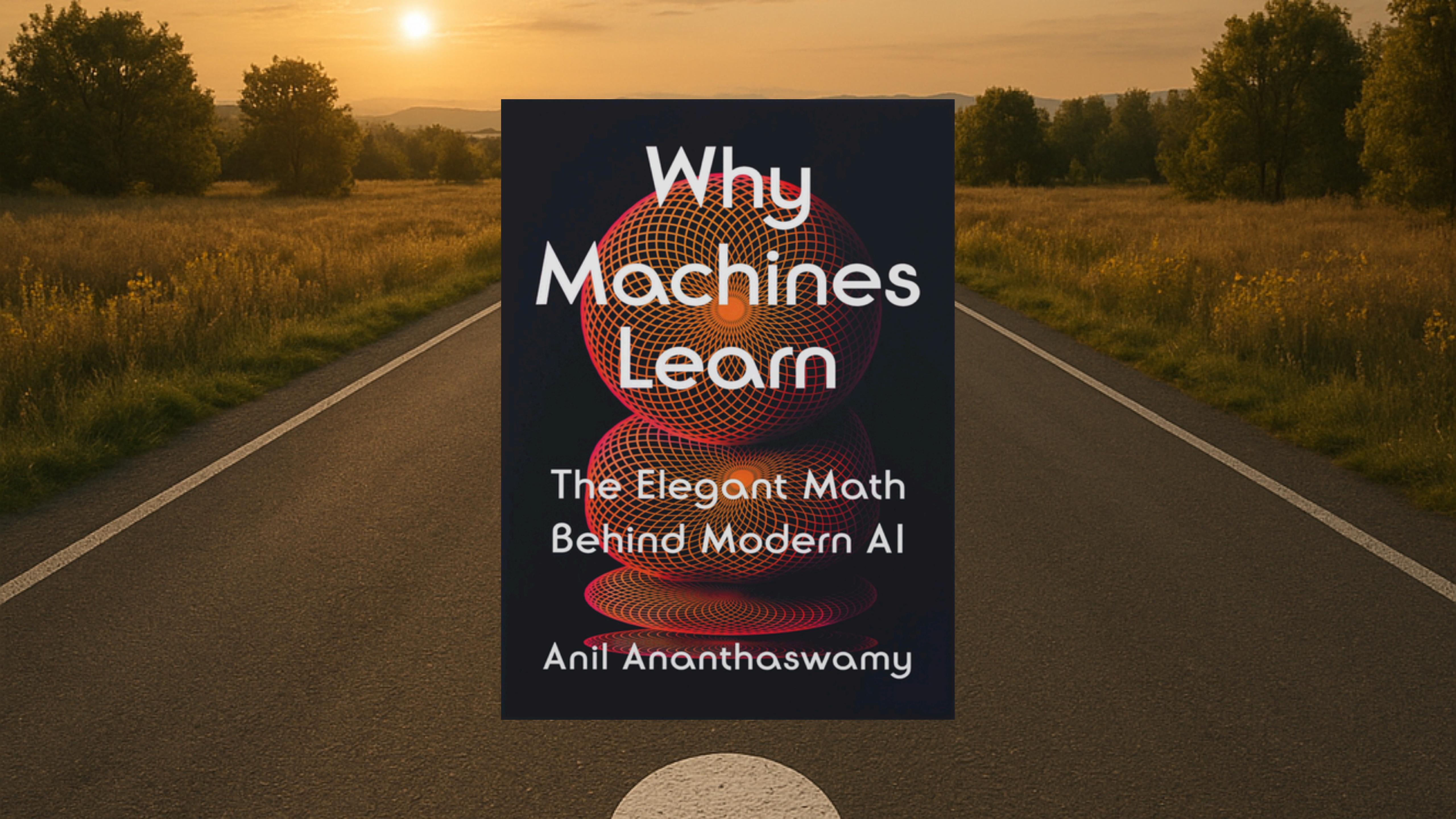
| # | Input1 | Input2 | Label |
|---|--------|--------|-------|
| 1 | 0.0 | 0.0 | -1 |
| 2 | 0.0 | 1.0 | -1 |
| 3 | 1.0 | 0.0 | -1 |
| 4 | 1.0 | 1.0 | 1 |

| Pixel1 | Pixel2 | Pixel3 | Pixel400 | M/F |
|---------------|---------------|---------------|-----------------|---------------|
| 0.43423423 | 0.74342342 | 0.5568449 | 0.25548439 | 1 (F) |
| 0.94324324 | 0.43423423 | 0.8887677 | 0.74342342 | -1 (M) |
| 0.74342342 | 0.25548439 | 0.02783833 | 0.43423423 | -1 (M) |
| 0.35454545 | 0.8887677 | 0.43423423 | 0.5568449 | 1 (F) |

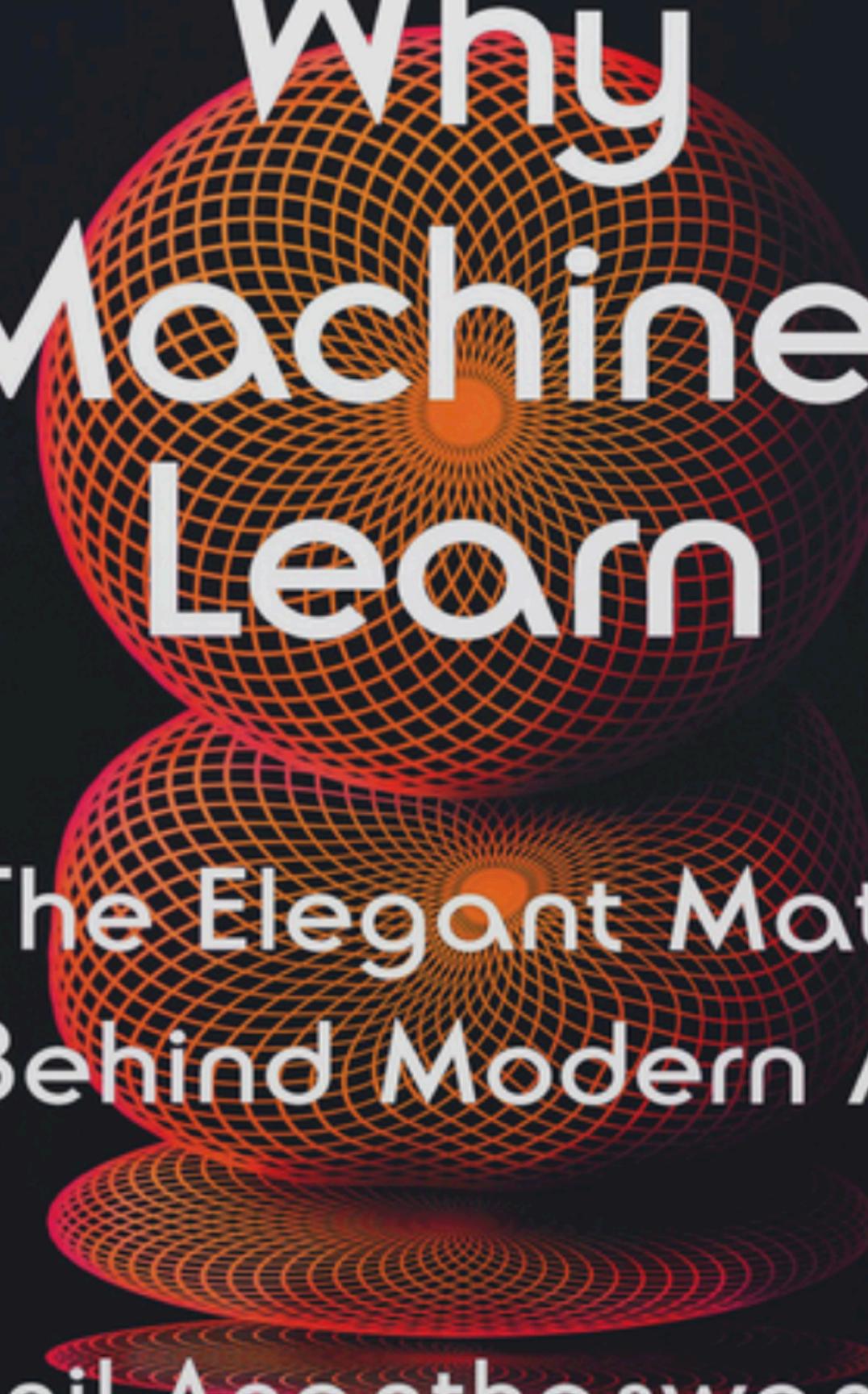
Demo 3

Recap

- Perceptron: Binary linear classifier
- Weights: How important each input is
- Bias: The “threshold” a value has to cross
- Training: Tiny adjustments to reduce errors
- Model: The way neurons are connected, the “blueprint”
- Model: The weights and biases after training
- Parameters: Amount of learnable weights and biases

The background of the entire image is a photograph of a paved road curving through a field of tall grass and trees under a warm sunset sky.

Why Machines Learn

Two large, semi-transparent red wireframe spheres are centered on the book cover. The top sphere is positioned behind the title text, and the bottom sphere is partially visible below it, creating a sense of depth.

The Elegant Math Behind Modern AI

Anil Ananthaswamy



BUILD A

Large Language Model

Sebastian Raschka

MANNING

FROM
SCRATCH



Keep learning

Thank you!

