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THE PERCEPTRON: A PROBABILISTIC MODEL FOR INFORMATION STORAGE AND ORGANIZATION IN THE BRAIN [1]

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Presenter: Daniel Maturana

Frank Rosenblatt, PhD (1928 – 1971)

- Background: Psychology
- Undergrad, PhD and teacher at Cornell

Introduction: 3 questions about biological systems

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- The textbook linear perceptron is a special case!

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- Rosenblatt rejects symbolic logic and Boolean algebra as a suitable language for analysis of this system
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- Part of a deeper split between “discrete” A.I. and more “statistical” approaches.

Biological inspiration

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- However, argues other biological theories are not rigorous enough
- The perceptron is a concrete, testable model

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3. After exposure to large sample of stimuli, “similar” stimuli will activate same sets of cells.
4. Positive and negative reinforcement influences connection formation.
5. *Similarity* is not a necessary attribute of the stimuli, but depends on the perceiving system, which evolves though interaction with a given environment.

The organization of a perceptron

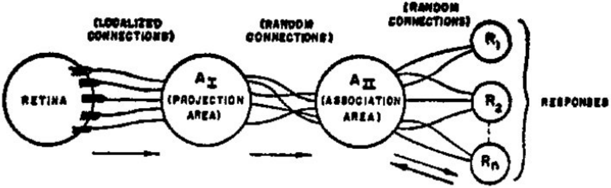

FIG. 1. Organization of a perceptron.

- S-points: sensory cells
- A-units: association cells
- R-units: response cells

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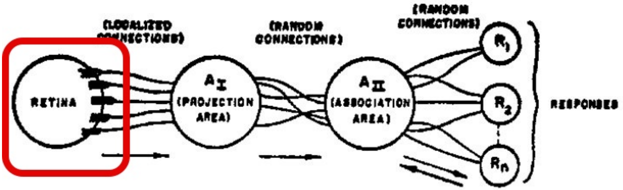

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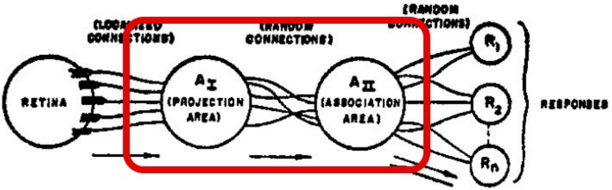

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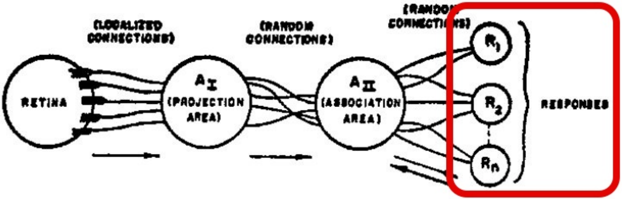

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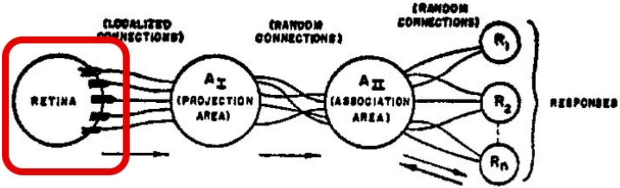


FIG. 1. Organization of a perceptron.

- “Sensory cells” activated by stimuli
- In practice modelled after the retina
- Activation is assumed to be discrete

A-units

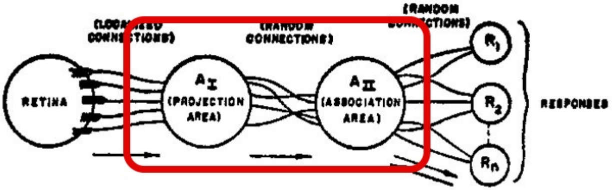
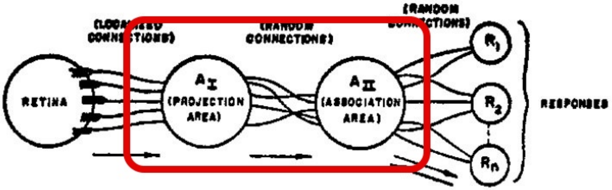


Fig. 1. Organization of a perceptron.

- “Association” units.
- Summation unit w/ threshold

$$\text{output} = \text{sgn}\left[\sum \text{excitatory} - \sum \text{inhibitory} - \theta\right]$$

A-units



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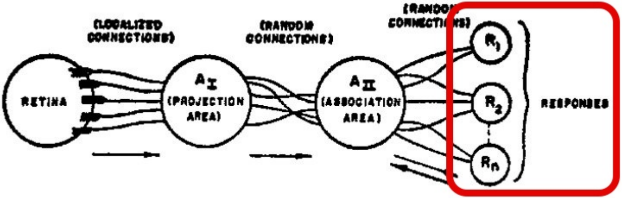
- A_1-units: receive connections from S-points. ("feature detectors")
- A_2-units: receive random input from A_1 units.



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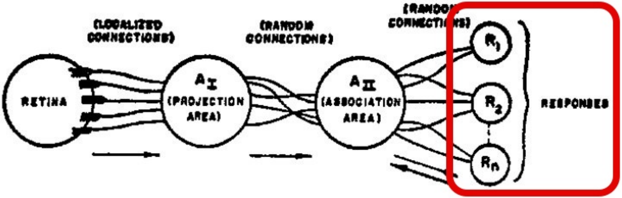

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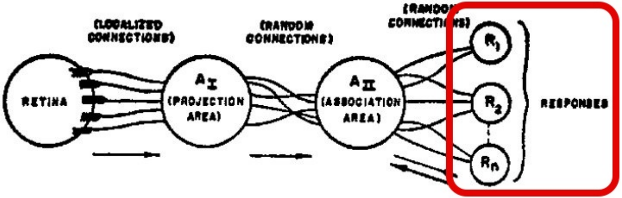
- "Response-cells", or output
- Reciprocal connections to A_2 cells.

R-units



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- "Response-cells", or output
- Reciprocal connections to A_2 cells.
- The feedback connections create a "winner-take-all" situtation

Learning with feedback

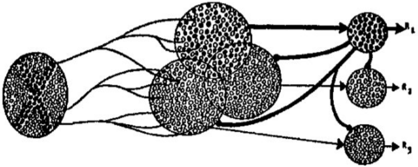

FIG. 3A. Predominant phase. Inhibitory connections are not shown. Solid black units are active.

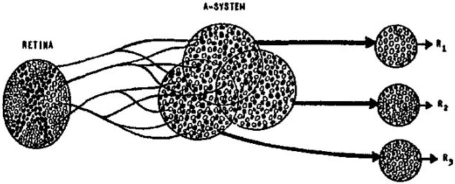

FIG. 3B. Postdominant phase. Dominant subset suppresses rival sets. Inhibitory connections shown only for R_1.

FIG. 3. Phases of response to a stimulus.

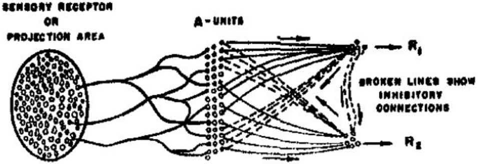

FIG. 2A. Schematic representation of connections in a simple perceptron.

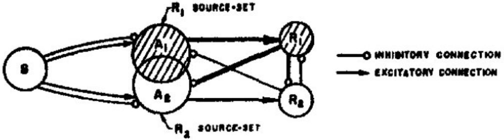

FIG. 2B. Venn diagram of the same perceptron (shading shows active sets for R_1 response).

The perceptron learning rule?

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- The paper considers and analyzes variations of the perceptron, none exactly the textbook perceptron

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- Similar to what we might call weights
- Biological meaning of “activation” is vague: it could be amplitude, frequency, latency, probability of transmission

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- Three systems with different value dynamics
    - α-system: each active cell gains unit activation
    - β-system: active cells gain a “mean” activation
    - γ-system: total activation is constant; active cells gain value, inactive cells lose value

- α-system is closest to the textbook perceptron, in “bivalent” variant (described below).

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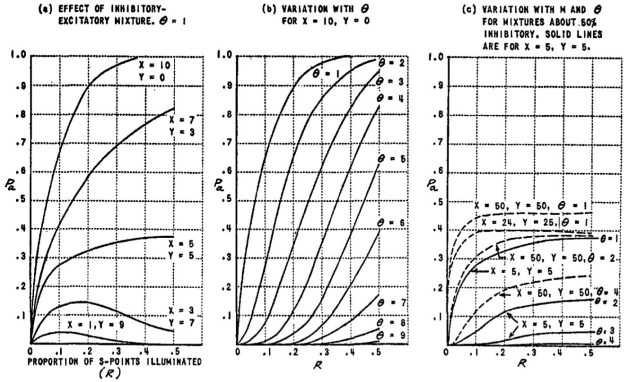
- Nothing has been said yet about supervised training
- Dynamic, “self-organizing” aspects not explored in this paper

Analysis of “predominant” phase

- Before learning takes place
- Questions:
  - How does parameters of perceptron affect activation?
  - How does characteristics of stimuli affect activation?

Analysis of “predominant” phase

- Focuses on two quantities:
  - P_a: expected proportion of A-units activated.
  - P_c: conditional probability that A-unit that responds to stimulus S_1 responds to another stimulus S_2.



Depends on threshold θ, size of stimuli and type of connections

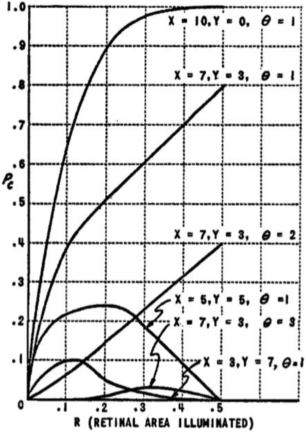


FIG. 5. P_c as a function of R, for nonoverlapping stimuli.

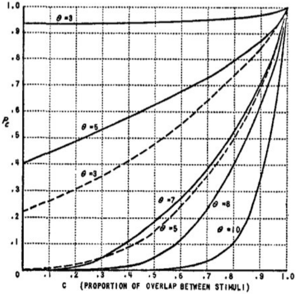


FIG. 6. P_c as a function of C. $X = 10$, $Y = 0$. Solid lines: R = .5; broken lines: R = .2.

Depends mostly on overlap between stimuli

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- Two experiments are considered, “ideal” (memorize random stimuli) and “differentiated” (learn “classes”).
- Analysis of expected probability of correct recall (for ideal case) and correct generalization (for differentiated case).
- Basic equation is

$$P = \left(1 - (1 - P_a)^{N_s}\right) \phi \left(\frac{c_1 n_{s_r} + c_2}{\sqrt{c_3 n_{s_r}^3 + c_4 n_{s_r}}} \right)$$

with constants depending on details of the experiment.

An “ideal” experiment

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Results of “ideal” experiment

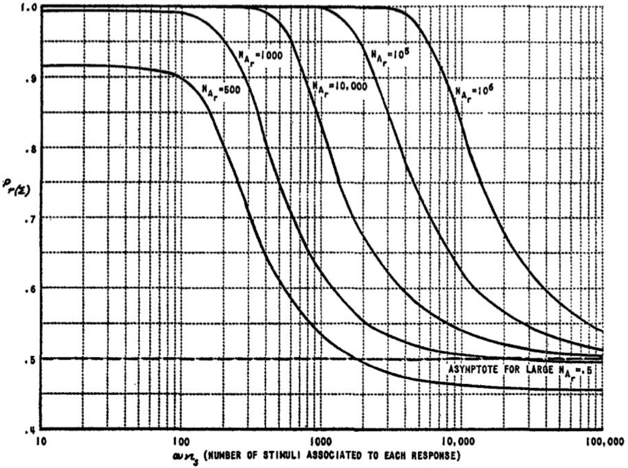

FIG. 7. $P_r(\Sigma)$ as function of ωn_s, for discrete subsets. ($\omega_c = 0$, $P_a = .005$. Ideal environment assumed.)

Performance gets worse as samples increase.

Results of “ideal” experiment

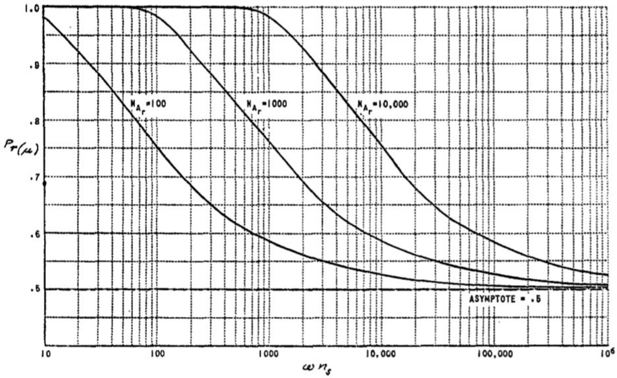

FIG. 8. $P_{r(\mu)}$ as function of ωn_s. (For $P_a = .07$, $\omega_c = 0$. Ideal environment assumed.)

Results of “ideal” experiment

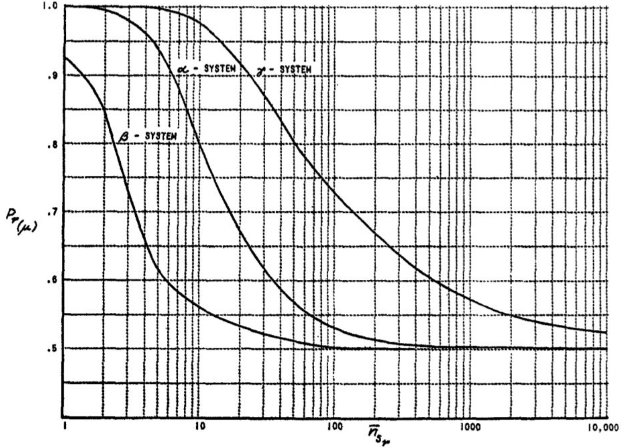

FIG. 10. Comparison of α, β, and γ systems, for variable n_{s_r} ($N_R = 100$, $\sigma_{n_{rs}} = .5\bar{n}_{s_r}$, $N_A = 10{,}000$, $P_a = .07$, $\omega = .2$).

Results of “ideal” experiment

- Empirically γ-system seems better
- Empirically μ rule is better, except for γ-systems

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4. After learning, test if system can generalize labels to unseen stimuli

From equation of expected recall/generalization, as $n_s \to \infty$,

$$P = \left(1 - (1 - P_a)^{N_s}\right) \phi \left(\frac{c_1}{\sqrt{c_3}} \right)$$

> *"In the limit it makes no difference whether the perceptron has seen a particular test stimulus before or not; if the stimuli are drawn from a differentiated environment, the performance will be equally good in either case."*

- Let $P_{c\alpha\beta}$ be the expected value of P_c for pairs of stimuli drawn from classes α and β

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- If $P_{c11} > P_a > P_{c12}$, performance of perceptron as samples tend to infinity will be better than chance.

Results of “differentiated” experiment

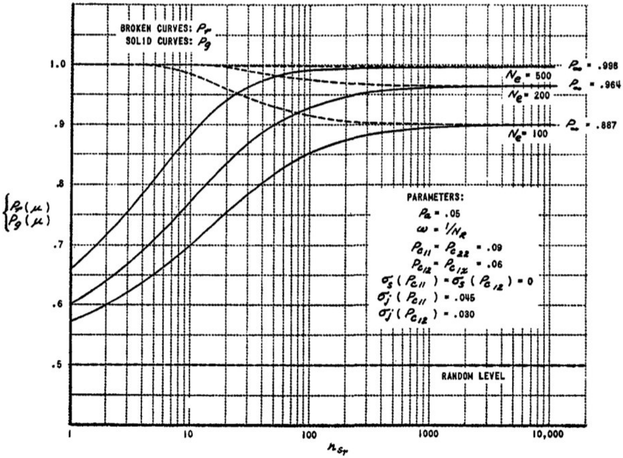

FIG. 11. P_r and P_g as function of n_{s_r}. Parameters based on square-circle discrimination.

Some notes

- No analysis of what kind of things can be learned
- No analysis of convergence
- Advocates use of binary coding (as opposed to one hot) for better performance with large number of responses

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- with α-system, most similar to the textbook perceptron!

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- Consideration of time, to analyze velocities, sequences, etc.

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- Intermodal (audio/photo) association

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- But bad at “relative judgment” and “abstraction of relationships”.
- Similar to “brain-damaged patients”.

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    - Proportion of R-units to which each A-unit connects
    - Number of A-units
    - Number of R-units
- The model is parsimonious, verifiable and of high explanatory power.

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- Drawbacks
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  - Practical and theoretical performance limitations