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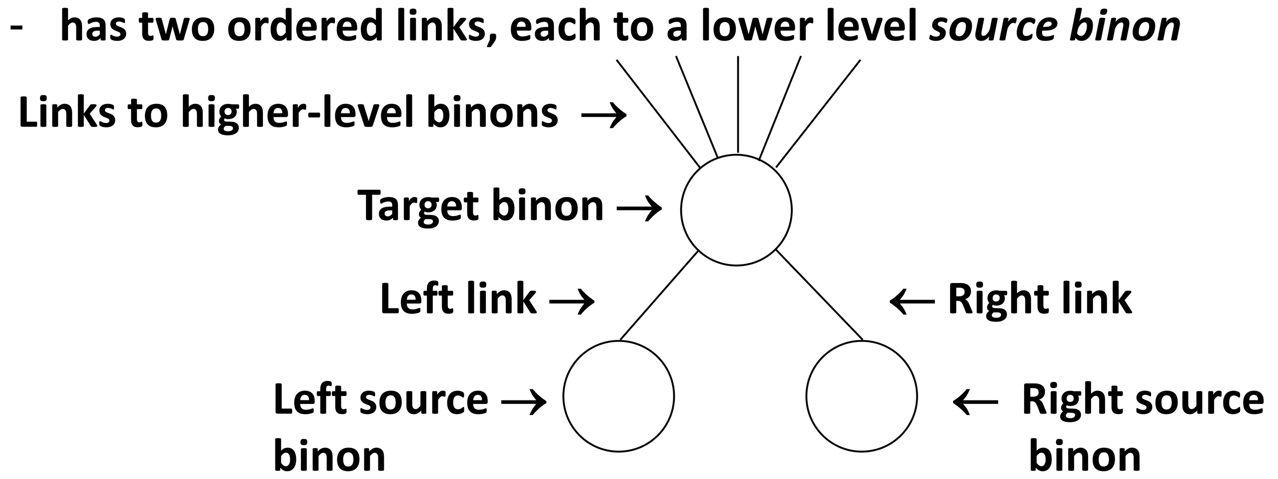
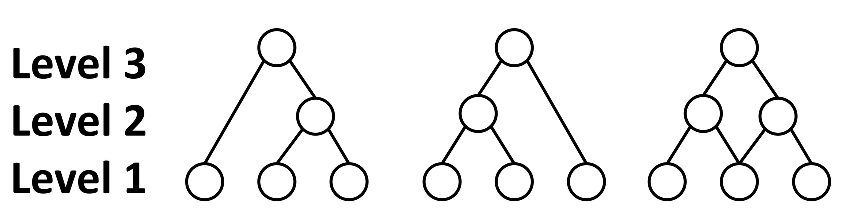
Perceptra: A New Approach to Pattern Classification Using a Growing Network of Binary Neurons (Binons)

Perceptra is a simple pattern classification algorithm that uses a compositional hierarchy of binary neurons called binons. Each binon represents a class or category. General categories are lower in the hierarchy and more specific combinations of categories are higher in the hierarchy. For pattern classification the lowest level binons represent features extracted from stimuli. These features are the invariant shape and contrast patterns formed from the ratios between the widths and intensities of the perceived objects. These ratios are calculated by subtracting the logarithms of their values as described in the Weber-Fechner Law. Perceptra starts with no binons and adds new binons to its network based on the coincidence and novelty of the features and their combinations. Its simplicity allows it to scale well over multiple levels of abstraction. It is sense independent and multimodal. It achieved over an 80% recognition rate on handwritten digits mapped onto a one-dimensional array of 64 sensors.

- **Pattern classification in AI — implicit category learning in cognitive science**
- **Perceptra grows a compositional hierarchy of binary neurons (binons)**
- **A binon is a node that represents a *class* or *category***
  - **has two ordered links, each to a lower level *source binon***

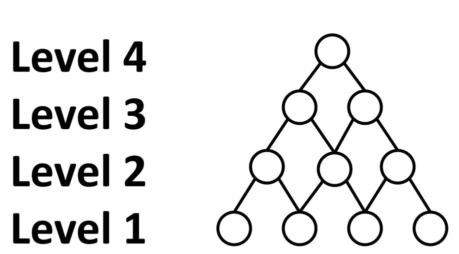


- **Source and target binons form a hierarchical network structure**
- **All the connections are "has-a" / "is part of" links**
- **Higher level binons represent more specialized categories**
- **Lower level binons represent more general categories**
- **Two source binons are *associated* when linked to the same target binon**
- **Lowest level binons represent the simplest shape and contrast features**



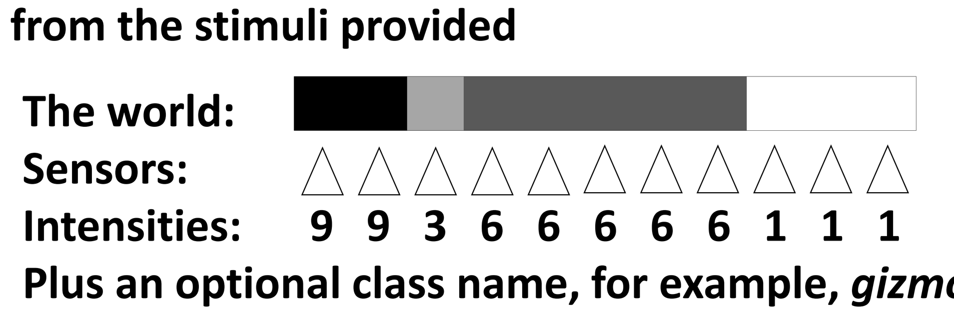
Possible hierarchies for representing three level 1 binons

- **Right-most structure is simpler**
  - **represents both pairs at level 2 and the triplet at level 3**
  - **restricts links to adjacent levels**



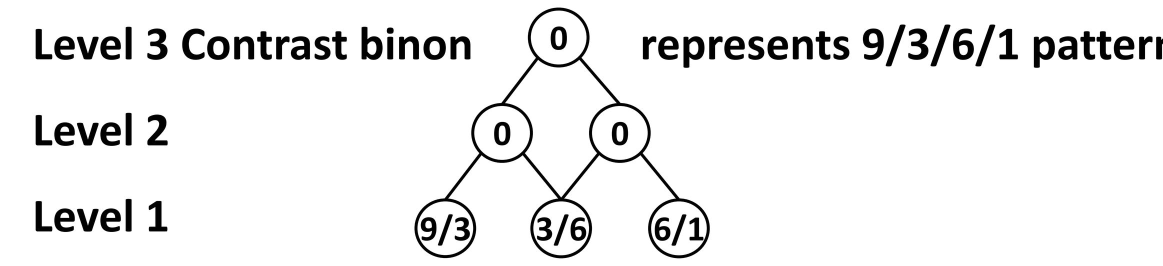
A compositional lattice of binons

- **The long-term memory for representing and recognizing categories of objects**
- **The lowest level categories are grounded on sensory data**
  - **extracted from the stimuli provided**

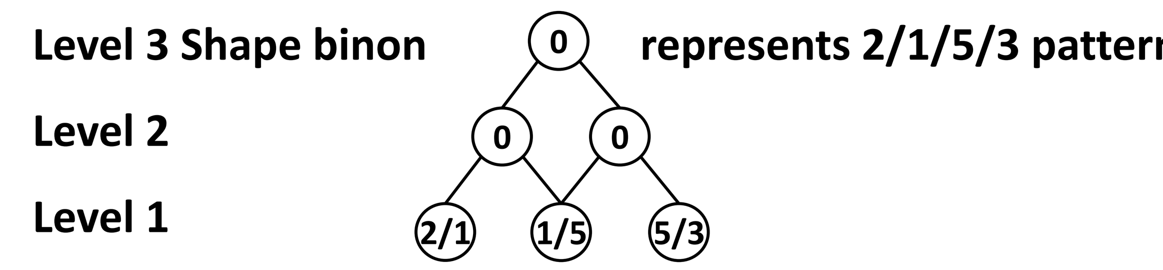


Example of an 11 sensor stimulus & class name

- **Smallest possible invariant features = most generic *patterns***
- **Note: No links between level 1 binons and the sensors**

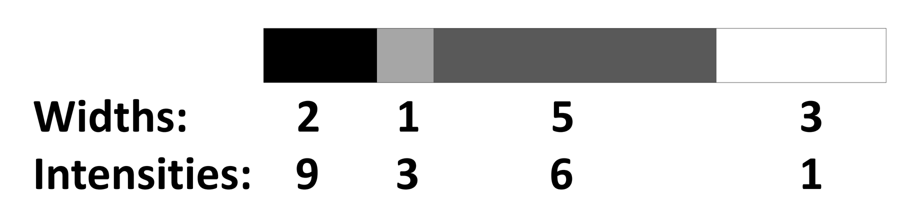


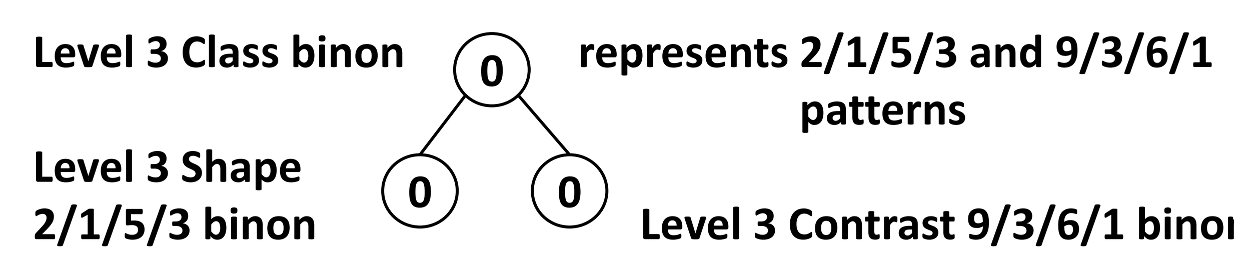
Contrast patterns - ratios of adjacent intensities



Shape patterns - ratios of adjacent widths

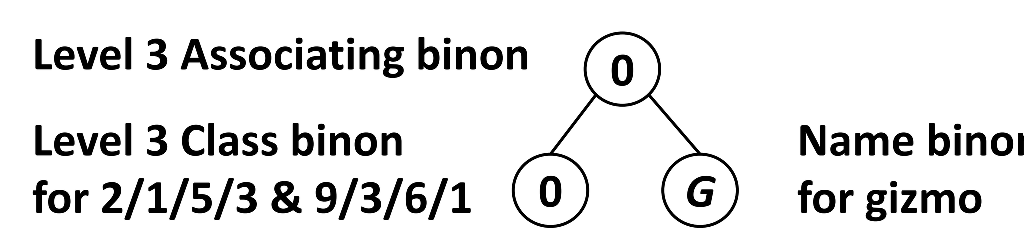
- ***Property binons* for each property type**
- **Calculated ratios kept in level 1 binons**
- **Values in higher level binons not necessary - set to zero**
- **Weber's Law - the just noticeable difference (JND) between two stimuli is proportional to the magnitude of the stimuli**
- **Fechner's law - human subjective sensation is proportional to the logarithm of the stimulus intensity**
- **Use** $\log(a/b) = \log(a) - \log(b)$
- **Use the integer of the resulting log value**
- **A log base of 1.2 will provide for a 20% JND**
- $\log_{1.2}(100/101) = 25.259 - 25.313 = -0.054$ and $\text{integer}[-0.054] = 0$
- $\log_{1.2}(100/120) = 25.259 - 26.259 = -1$
- **100/120 to 100/143 produce the same value (-1)**
- **Property binons combined to produce *class binons***





An association of shape and contrast patterns

- **Symbolic representations of categories of ratios**
- **Multimodal - if include properties from other senses**
- **The gizmo class name is a symbolic value**



A class binon associated with its class name

- **No associated name binon → unclassified class binon**
- **One name binon → unique classification (unambiguous)**
- **More than one name binon → ambiguous classification**

- **Perceptra's data structures**
  1. **Stimulus**
  2. **Activation tree per stimulus (Short Term Memory)**
     - **Logarithmic values of sensor readings and derived values such as width**
     - **References to the categories (binons) found in the stimulus**
  3. **Growing binon network (Long Term Memory)**

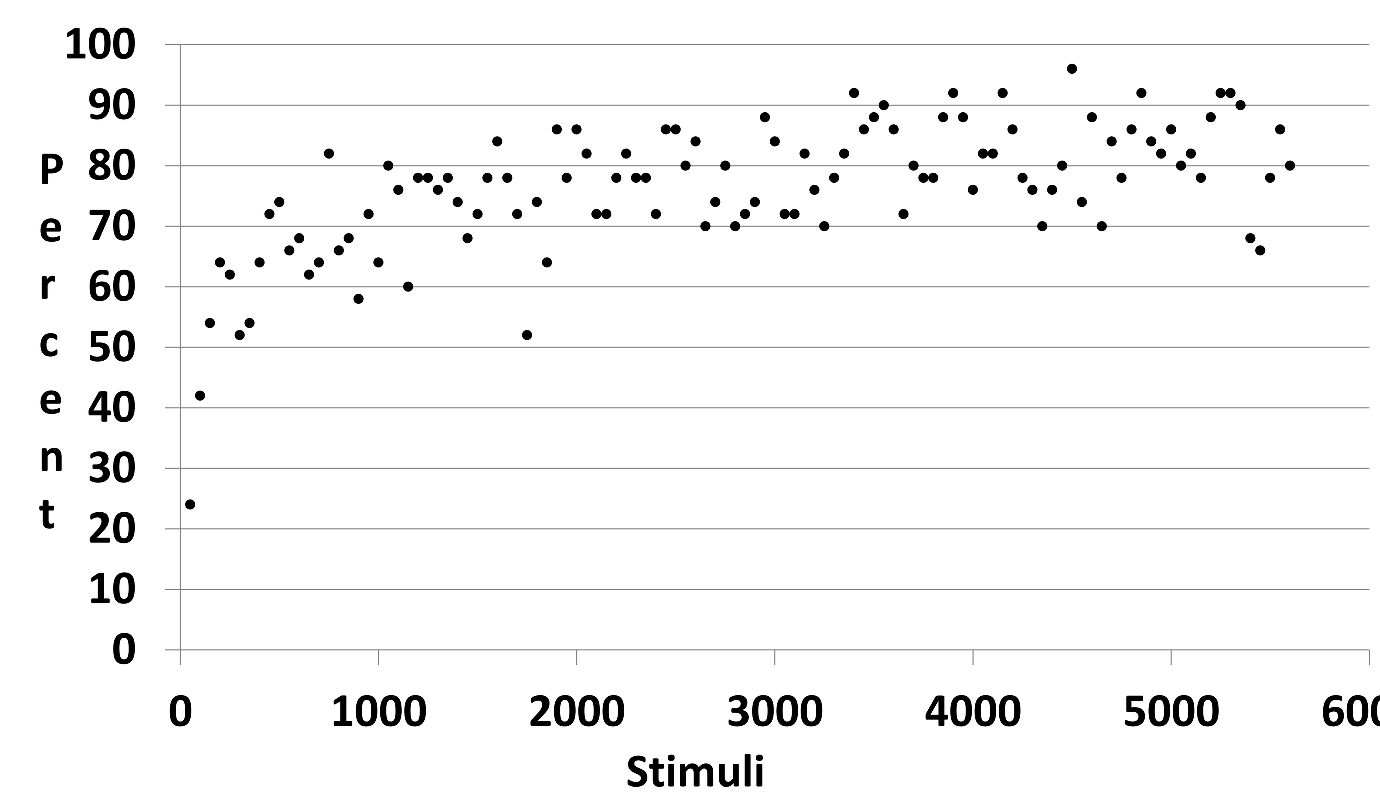
- **Perceptra's two learning rules:**
  1. **Combine source binons when they occur in the same stimulus**
     - **Learning based on coincidence and novelty - Hebbian learning rule**
  2. **Combine familiar binons – only reuse known patterns**
     - **Avoids the combinatorial explosion of binons at higher levels**

- **The classification process**
  1. **Start with an empty binon network**
  2. **For each stimulus**
     - **2.1 Create the leaf activation tree entries for each part**
     - **2.2 Find existing or create new level 1 property binons**
     - **2.3 At each level combine familiar source binons or create new ones**
       - **2.3.1 Find existing property binons or create new ones**
       - **2.3.2 Find existing class binons or create new ones**
     - **2.4 Predict the category from the most frequently occurring name binon associated with the unambiguous binons**
     - **2.5 Associate all the found and new binons with the given name binon**

- **Handwritten digit recognition**

Example 8x8 UCI images and bitmaps

- **Horizontally rasterized onto a one dimensional array of 64 sensors**
- **First row recognition rate — 65%**
- **Second row recognition rate > 80%**



Percent correct prediction using a JND of 20%

- **5600 stimuli - 45,137 shape binons created**
- **Level 6 - 9,394 shape binons created**
- **Level 8 - most frequently used level for prediction purposes - 78% correct**
- **Level 12 - 455 binons created - 88 predictions made - 96% correct**

- **Still needs to be tested on a wider variety of tasks**
- **Pruning strategy may be necessary on larger datasets**
- **Recognizing rotations, reflections and inversions is not built-in**

- **Uses a simple component in a simple structure**
- **A deterministic approach - no stochastic, probability or statistical inference**
- **Multimodal**
- **Graduated or Symbolic stimuli**

Conclusion

The power of a compositional hierarchy of categories and very simple mathematics, logarithms and subtraction, are sufficient to perform implicit category learning.

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