Learning Category Instances and Feature Utilities in a Feature-Selection Model

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Autonomous Systems

- Perceptual systems tend to feed forward to cognitive systems that provide little feedback
- Establish a feedback loop between perceptual and cognitive systems
- Exploit cognitive context to augment bottom-up perceptual approaches
Intent

• ACT-R = a priori architecture of ML methods
  • Traditionally, ML methods tailored to problem ad-hoc
  • Classification & Feature Selection usually treated separately

• Create generic cognitive module for classifying objects, scenes or situations
  • Feature Selection Model (YACM)
  • FS Model = Prediction problem (which class) + Inference problem (important features)

• Design goals
  • Take input from any perceptual module
  • Learn to classify (Instance-Based Learning)
  • Learn which features to use (Feature Selection)
  • Stay close to architecture for generalizability
    • Respect default parameter values
    • Observe strict harvesting
  • Fixed representational scheme will not work
    • Flexible chunks in v7 make this easy
EGCM-RT (Lamberts, 2000) & EBRW (Nosofsky & Palmeri, 1997)

- Encode features one at a time until a category decision is made
  - Decision depends on similarity b/t S & instances in memory
  - S representation gradually constructed via info accumulation process
  - Accumulation stops as function of evidence for category membership

- Retrieved exemplars during info accumulation drive a random walk process
  - Implies a random walk pointer
  - Exemplars retrieved until pointer exceeds criterion value for 1 of classes
Feature Selection Model

- Combine IBL w/FS to anchor perceptual labels
- S information accumulated in imaginal buffer
- Make class inference for each feature encoded
- Random walk pointer & criterion value represented by relative utility of & competition among encoding & decision productions

Declarative Memory
- IBL
- Prediction problem

Procedural Memory
- R-L
- Inference problem

Infer label given observed features

Utility

Encode feature given label

Classify exemplar
Cohn-Kinade Facial Expressions

Similarity of emotion labels based on shared AUs (features).

Emotion x Feature network indicates that emotion labels are associated with both shared- and distinct facial Action Units. Categorization depends on different subsets of overlapping and non-overlapping features.
Baseline: Retrieve Exemplars

That's 20% correct

Proportion correct for sliding window 100 trials wide

Anger everywhere

Activation
:blt nil
:mas 10
:ans nil

Utility
Reward 10, -1
:alpha 0.2
:egs 0

10,000 trials
188 chunks
Retrieve Exemplars w/Noise

That's 25% correct

Noise improves response variability

<table>
<thead>
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<th>1</th>
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</thead>
<tbody>
<tr>
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<tr>
<td>unknown</td>
<td>16</td>
<td>0</td>
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</table>

Activation: bll nil :mas 10 :ans .25
Utility: Reward 10, -1 :alpha 0.2 :egs 1.0

3695 chunks
That's 50% correct

Mix of exemplars & prototypes yields better performance

11,562 chunks
Augment Context Effect

Activation
:blt nil
:mas 10
:ans .25
:tmp 10

Utility
Reward 10, -1
:alpha 0.2
:egs 1.0

That's 60% correct

11,591 chunks
Confusions After 9000 Trials

Overgeneralization
Many false alarms
Control Reward Distribution

That's 80% correct

Distribute NULL rewards when inferred class changes

Add "guessing" productions for when inferred class changes just before conclusion is drawn.

Activation
:bl1 nil
:mas 10
:ans .25
:tmp 10

Utility
Reward 10, -1
:alpha 0.2
:egs 1.0

9721 chunks
Confusions After 9000 Trials

Fewer false alarms
Class-specific Decisions

Add 1 decision & 1 "guessing" production for each class as a means for representing costs/benefits associated with particular decisions.

That's 80% correct

Activation:
:bll nil
:mas 10
:ans .25
:tmp 10

Utility
Reward 10, -1
:alpha 0.2
:egs 1.0

10,161 chunks
Confusions After 9000 Trials
# Feature Counts by Class

**Data:** Feature presence only

**Model:** Feature present or absent

<table>
<thead>
<tr>
<th>Feature Response</th>
<th>Count Statistics</th>
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<tbody>
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<td>Min. 2.00</td>
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<td>Min. 1.00</td>
</tr>
<tr>
<td>fear</td>
<td>Min. 6.00</td>
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<tr>
<td>happy</td>
<td>Min. 1.0</td>
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<tr>
<td>sadness</td>
<td>Min. 4.00</td>
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<tr>
<td>surprise</td>
<td>Min. 0.00</td>
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</table>
Gold & Coal

• Gold Nugget
  • Flexible chunks
  • Link b/t symbolic & subsymbolic representation
  • Subsymbolic learning that is a mix of traditional ML methods

• Lump of Coal
  • Lack of a "simulated annealing" process in R-L
  • Rewards tied to time scale
  • Lack of production-specific exploitation/exploration