# **RULEX-EM:**

Incorporating exemplars and memory effects in a hypothesis-testing model of category learning



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*Acknowledgements* Robert E. Wray

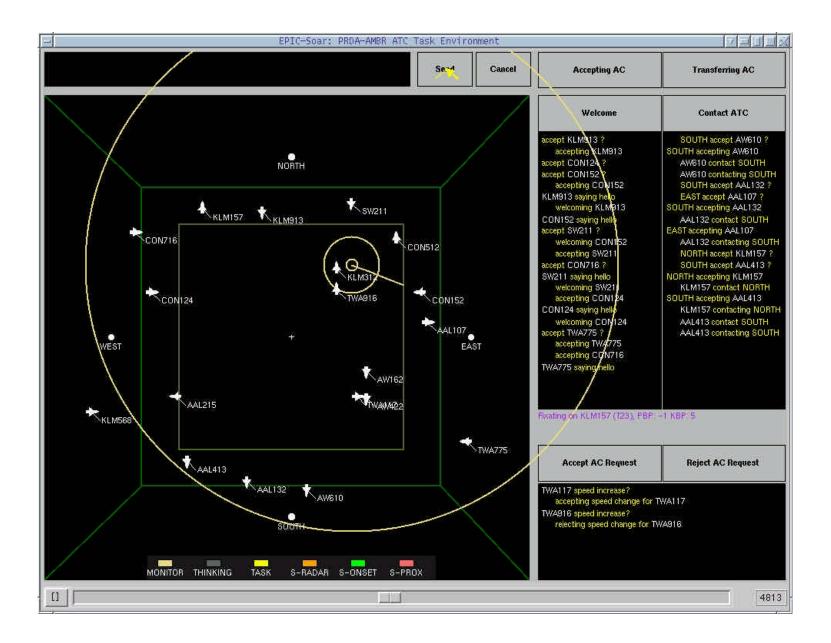
# Modeling with EASE (Elements of ACT-R, Soar, and EPIC)



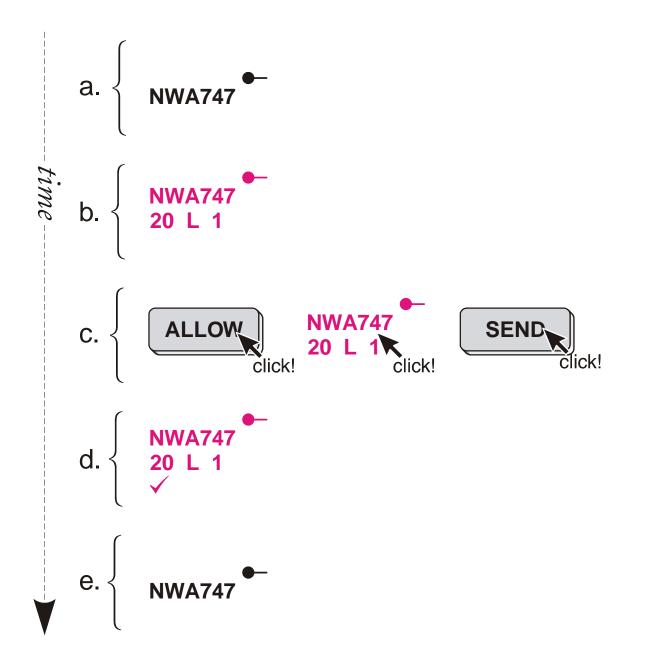
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#### DEMO: THE TASK



#### SCHEMATIC OF A CATEGORY LEARNING TRIAL



# • Category task:

- Three features with two values each: FUEL (20 or 40), SIZE (L or S), TURBULENCE (1 or 3)
- Eight possible instances; 2<sup>3</sup>
- Category is either ALLOW or DENY with four instances in each category

# • Three categorization problems *types*:

- Type 1: category is defined by a single dimension; e.g. if SIZE is L, then ALLOW. This is the easiest problem
- Type 3: can be characterized as requiring a single-feature rule, plus exception rules.
- Type 6: the most complex category; all features are relevant; correct rules must test three features.

### CATEGORY TASK DETAILS, CONT'D

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• Type 1

FUEL	SIZE	TURB	CATEGORY
20	S	1	Accept
20	S	3	Accept
20	L	1	Accept
20	L	3	Accept
40	S	1	Reject
40	S	3	Reject
40	L	1	Reject
40	L	3	Reject

### CATEGORY TASK DETAILS, CONT'D

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• Type 3

FUEL	SIZE	TURB	CATEGORY
20	S	1	Accept
40	S	1	Accept
40	L	1	Accept
20	S	3	Accept
20	L	3	Reject
40	S	3	Reject
40	L	3	Reject
20	L	1	Reject

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• Type 6

FUEL	SIZE	TURB	CATEGORY
20	S	3	Accept
20	L	1	Accept
40	S	1	Accept
40	L	3	Accept
20	S	1	Reject
40	S	3	Reject
40	L	1	Reject
20	L	3	Reject

- Existing models that have been fit to Nosofsky's data:
  - RULEX, ALCOVE, Configural Cue, Configural Cue w/ DALR, SUSTAIN, rational model
- Why not use an existing category learning model?
  - Very few are process models
  - None are implemented in a cognitive architecture
  - Time-to-categorize is not a typical output of these models
  - Lots of free parameters; as many as ten in one model
  - Few hybrid models (containing both exemplars and rules)
  - Few models represent memory effects (forgetting)
  - None are sensitive to time; e.g. inter-stimulus time
  - None are sensitive to the presence of a secondary task
- Goal: Build a model that does all this

- A process model
- Implemented in a cognitive architecture (EPIC-Soar)
- Inspired by RULEX, a hypothesis-testing process model
- Incorporates rules and exemplars
- Forgetting, using an ACT-R mechanism
- Uses a smaller set of parameters
- "-EM" means Exemplars and Memory constraints

#### ACTIVATION AND DECAY MECHANISM

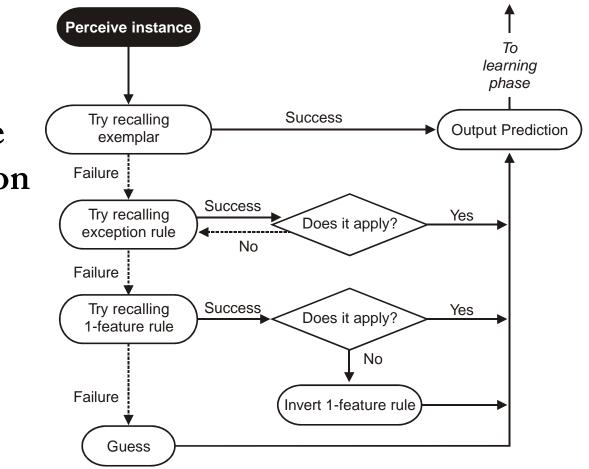
- Derived from ACT-R's mechanism
- Parameters used for this model:
  - decay-rate = -0.5
  - transient noise = 0.25
  - retrieval threshold = 0.0
  - base-level constant = 1.0
- These are all ACT-R default parameters or commonly used values for ACT-R models.

#### KNOWLEDGE REPRESENTATION

- Like RULEX and other models, this model uses a homogeneous representation for exemplars and rules:
- Four-tuple:
  - One slot for each feature; e.g. fuel, size, turbulence
  - One for the category
- Two kinds of rules: single-feature and exceptions
- Examples:
  - *Exemplar*: [FUEL = 20; SIZE = S; TURB = 3; CATEGORY = ALLOW]
  - *Single-feature*:[FUEL = \*; SIZE = \*; TURB = 3; CATEGORY = ALLOW]
  - *Exception*: [FUEL = \*; SIZE = L; TURB = 3; CATEGORY = DENY]
- These structures are all subject to decay and forgetting.

#### PREDICTION PHASE

- Mostly inherited from RULEX
- Strict sequential use of category prediction strategies
- New part is "Try recalling exemplar"



#### PREDICTION PHASE: EXAMPLE TRACES

# Prediction by guessing on first trial...

```
1: 0: 01 (perceive-instance)
1: instance 0: 4000 L 3
2: 0: 02 (failed-episodic-recall)
2: unable to recall a classification
3: 0: 03 (failed-exception-rules)
3: unable to recall an exception
4: 0: 04 (failed-1-dim-rules)
4: unable to recall a 1-dim rule
5: 0: 06 (guess-reject)
6: 0: 07 (output-prediction)
```

6: sending prediction: R

## Generating a prediction by recalling the classification...

49420: 0: 01019 (perceive-instance)
49420: instance 64: 4000 S 3
49421: 0: 01020 (try-episodic-recall)
49421: successfully recalled the classification: R
49422: 0: 01022 (output-prediction)
49422: sending prediction: R

#### PREDICTION PHASE: EXAMPLE TRACES

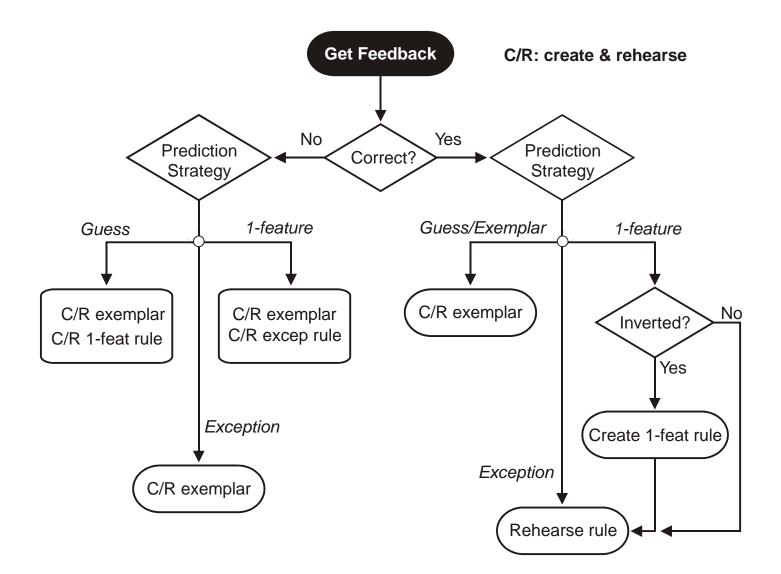
### Using a one-dimension rule....

```
7587: 0: 0136 (perceive-instance)
7587: instance 10: 4000 S 1
7588: O: O137 (failed-episodic-recall)
7588: unable to recall a classification
7589: 0: 0138 (failed-exception-rules)
7589: unable to recall an exception
7589: available 1-dim rule: (size L => A)
7590: 0: 0139 (try-1-dim-rules)
7590: attending to most active rule: (size L ==> A)
7591: 0: 0139 (try-1-dim-rules)
7591: it looks like i can use this rule.
7592: 0: 0139 (try-1-dim-rules)
7592: it cannot be applied directly; will invert
7593: 0: 0139 (try-1-dim-rules)
7593: will try the inverted form instead: (size S ==> R)
7594: O: O141 (output-prediction)
7594: sending prediction: R
```

Demonstrates strategy of "inverting" a one-dimension rule.

## Using an exception rule...

```
14792: O: O275 (perceive-instance)
14792: instance 19: 4000 T. 3
14793: O: O276 (failed-episodic-recall)
14793: unable to recall a classification
14793: available exception rule: (size L turbulence 1 ==> R)
14794: 0: 0277 (try-exception-rules)
14794: attending to most active rule: (size L turbulence 1 ==> R)
14795: O: O277 (try-exception-rules)
14795: oops...rule cannot be applied
14796: O: O277 (try-exception-rules)
14796: available exception rule: (size S turbulence 3 ==> A)
14797: O: O279 (try-exception-rules)
14797: attending to most active rule: (size S turbulence 3 ==> A)
14798: O: O279 (try-exception-rules)
14798: winning exception rule cannot be applied
14799: O: O279 (try-exception-rules)
14800: 0: 0278 (failed-exception-rules)
14800: available 1-dim rule: (size S ==> R)
14800: available 1-dim rule: (size L ==> A)
14801: 0: 0280 (try-1-dim-rules)
```



# Memorizing and rehearsing exemplar...

1072: 0: 023 (guess-reject) 1073: 0: 024 (output-prediction) 1073: sending prediction: R 1074: 0: 025 (get-feedback) 1074: feedback on trial 1 : CORRECT 1075: 0: 026 (acknowledge-correct-prediction) 1076: 0: 027 (memorize-classification) 1076: associating correct prediction with the stimulus 1077: 0: 028 (rehearse-classification) 1077: rehearsing classification 1082: 0: 029 (clean-up)

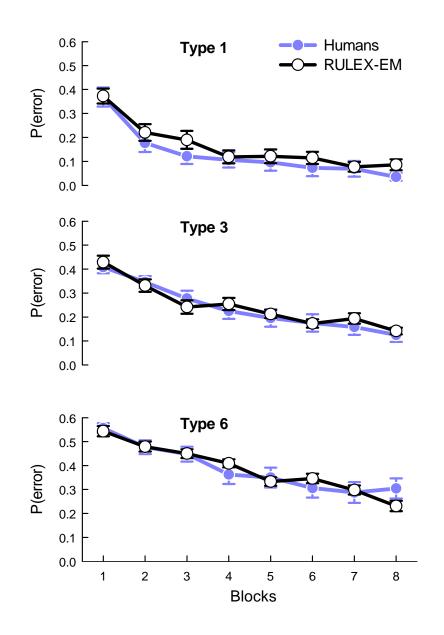
# Learning a 1-dim rule...

```
5: 0: 06 (quess-reject)
6: 0: 07 (output-prediction)
6: sending prediction: R
7: 0: 08 (get-feedback)
7: feedback on trial 0 : INCORRECT
8: 0: 09 (derive-correct-prediction)
9: 0: 010 (memorize-classification)
9: associating correct prediction with the stimulus
10: 0: 011 (rehearse-classification)
10: rehearsing classification
15: 0: 013 (sample-dim-for-1-dim-rule)
16: 0: 015 (create-1-dim-rule)
16: building 1-dim rule: elaborating size with L
17: 0: 015 (create-1-dim-rule)
18: 0: 015 (create-1-dim-rule)
18: memorizing 1-dim rule: (size L ==> A)
19: 0: 016 (rehearse-rule)
19: rehearsing rule: (size L ==> A)
27: 0: 017 (clean-up)
```

### Learning an exception rule...

```
17838: attending to most active rule: (size S ==> R)
. . .
17841: 0: 0341 (try-1-dim-rules)
17841: successfully applying the attended 1-dim rule
17842: O: O343 (output-prediction)
17842: sending prediction: R
17843: 0: 0344 (get-feedback)
17843: feedback on trial 23 : INCORRECT
17844: O: O345 (derive-correct-prediction)
17845: O: O346 (note-failed-dim-in-1-dim-rule)
17845: memorizing failed-dim-for-1-dim-rule: size
17846: rehearsing state-info: failed-dim-for-1-dim-rule size
. . .
17855: O: O349 (sample-1st-dim-for-exception)
17856: O: O350 (sample-other-dims-for-exception)
17857: 0: 0352 (create-exception)
17857: building exception: size S turbulence 1
17859: 0: 0352 (create-exception)
17859: memorizing exception rule: (size S 1 ==> A)
17860: 0: 0353 (rehearse-rule)
17860: rehearsing rule (size S 1 ==> A)
17868: 0: 017 (clean-up)
```

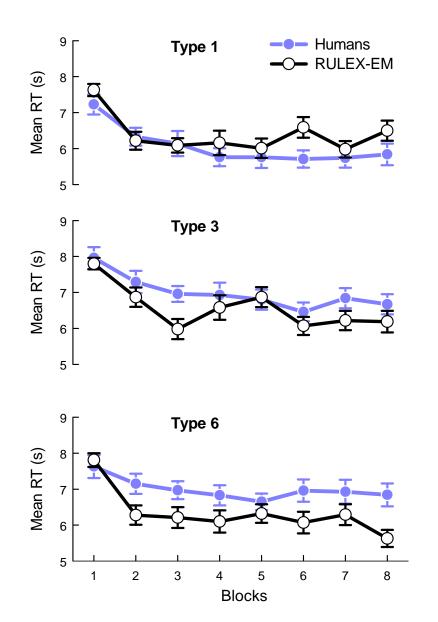
### LEARNING TASK: P(ERROR), AGGREGATE



• Satisfactory fit.

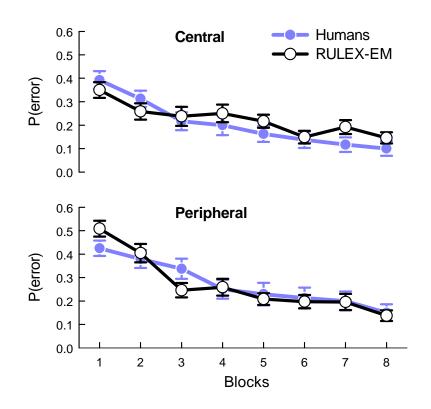
• 
$$G^2 = 5.64$$

#### LEARNING TASK: RESPONSE TIME



- SSE = 8.40
- Why is the model faster on Category 6?
  - Exemplar and exception-rule recall account for 80% of responses.
  - These are the first two prediction strategies, so prediction ends relatively early.

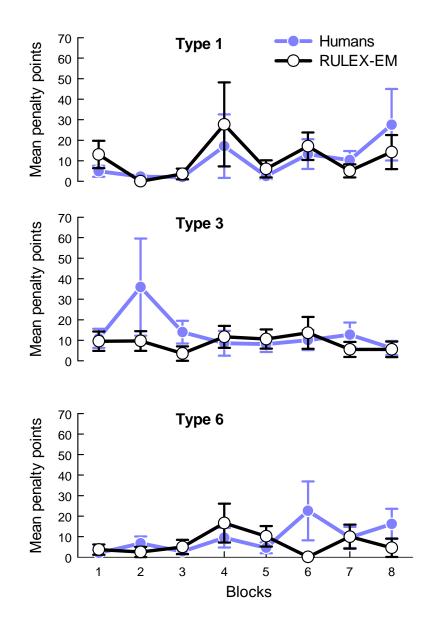
### LEARNING TASK: CENTRAL VS. PERIPHERAL



• Satisfactory fit.

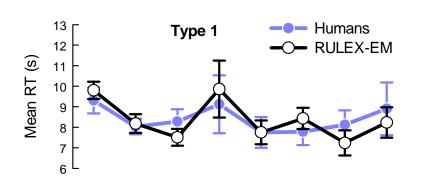
• 
$$G^2 = 5.89$$

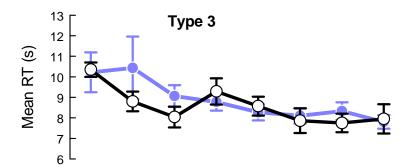
#### HAND-OFF TASK: PENALTY SCORE

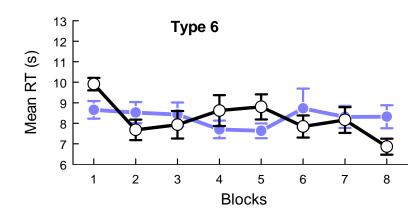


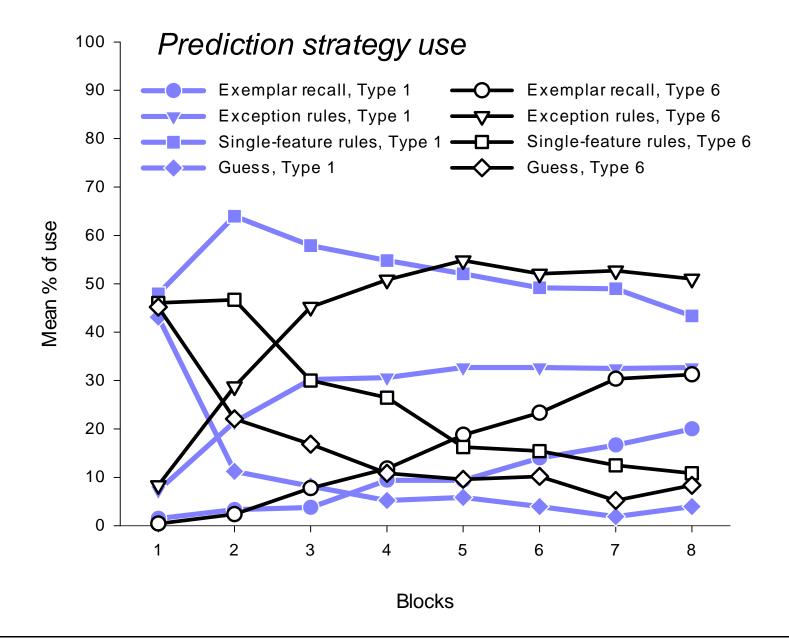
- SSE = 2046
- Notice that the model often gives a *qualitative* prediction of performance variability.

### HAND-OFF TASK: RESPONSE TIME









• One validation of EASE.

"...incorporating the mechanisms of other architectures and models and 'inheriting' their validation against human data promises to result in rapid progress as parallel developments by other architectures emerge." (Pew & Mavor, 1998, p. 95).

- Parameters manipulated to achieve fits:
  - # of rehearsals for memorizing exemplar; final value = 4.
  - # of rehearsals for memorizing rules; final value = 7.
- Model was *fitted* only to P(error) by problem type; all others were *predictions* of the model.
- Tons of empirical category learning data for further validation.

- Tons of empirical category learning data for further validation.
- Does not capture the different strategies subject make take; i.e. "On this trial, I'm just going to memorize the stimuli."