Semi-Automatically Evolving CHREST Models of Verbal Learning

Fernand Gobet

Dmitry Bennett, Noman Javed, Laura Bartlett, Peter Lane

LSE THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

erc European Research Council

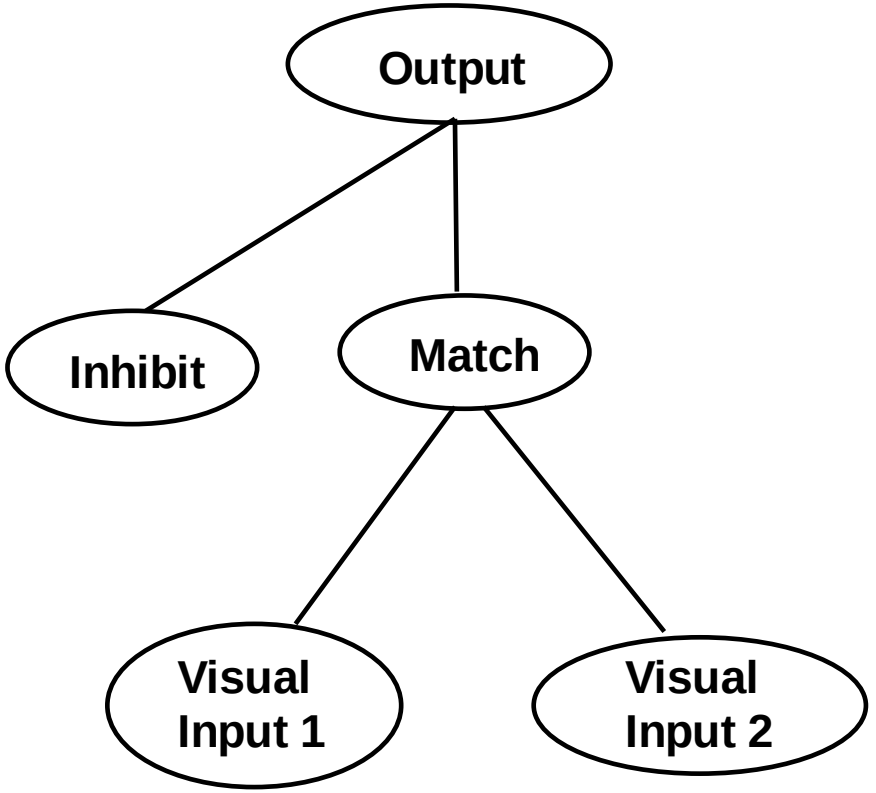
Funding for top researchers from anywhere in the world

Outline

- Using evolutionary computation to semi-automatically evolve models
  - GEMS (Genetically Evolving Models in Science)
- Using GEMS with a (simple) cognitive architecture
  - CHREST
- Applying the combined approaches to verbal learning
  - Verbal learning B I J → FOZ
  - Results of simulations
  - Comparison with a handcrafted cognitive model

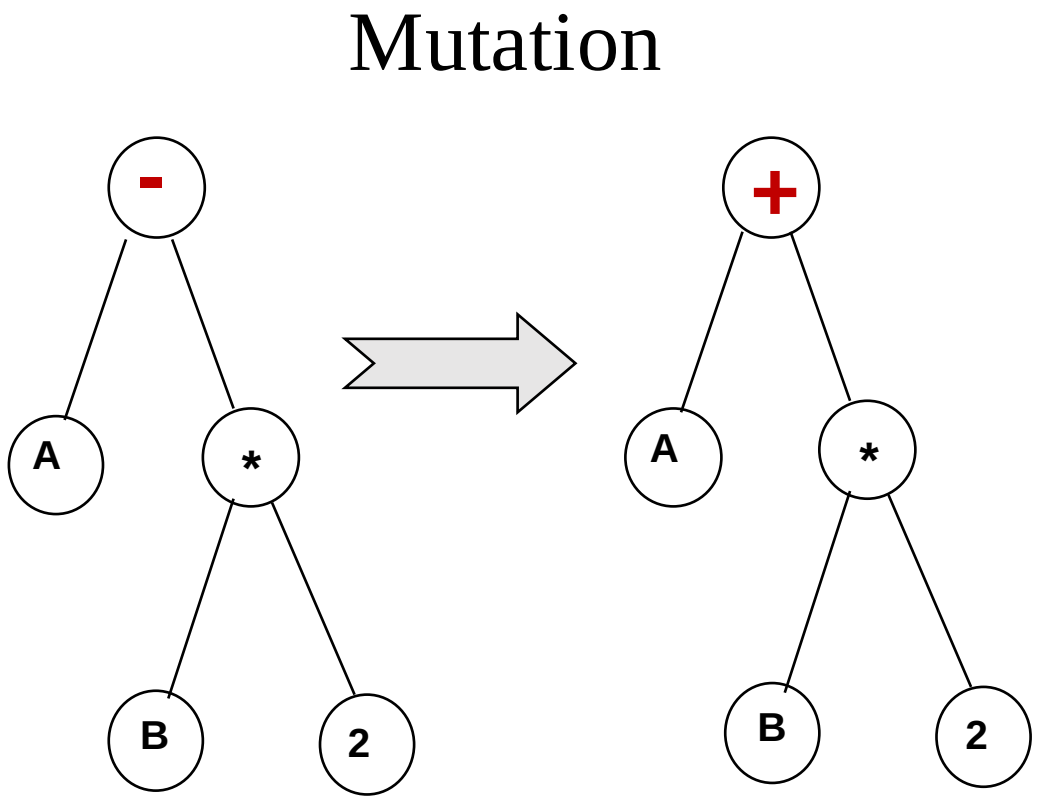
Cognitive Psychology Theories as Computer Programs

- Cognitive theories can be represented as computer programs
- These theories can be represented as trees
- These programs (trees) can be evolved

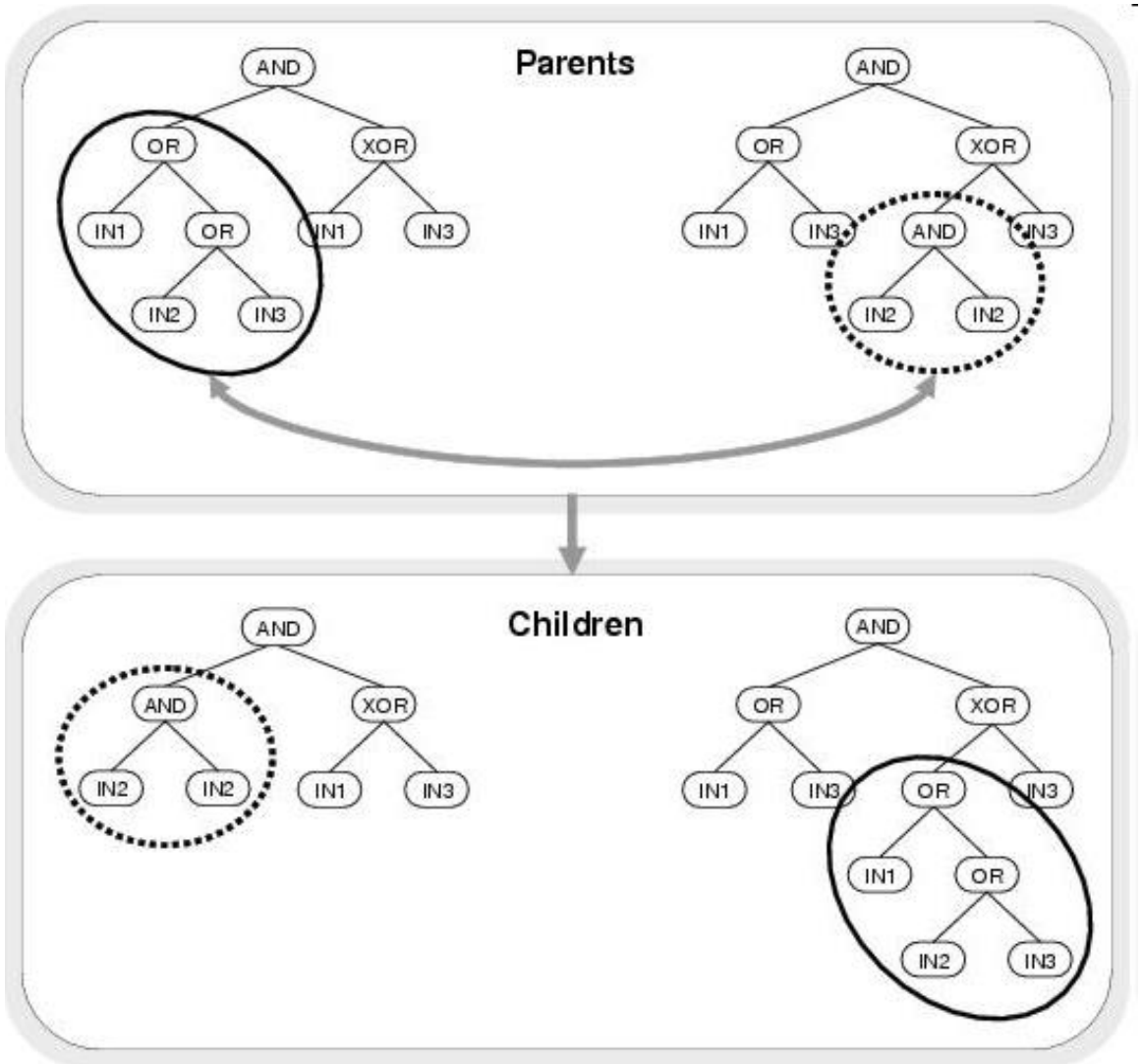


Genetic Programming (GP)

- Breeds and evolves entire computer programs
- Three main mechanisms
  - Selection
  - Mutation
  - Crossover



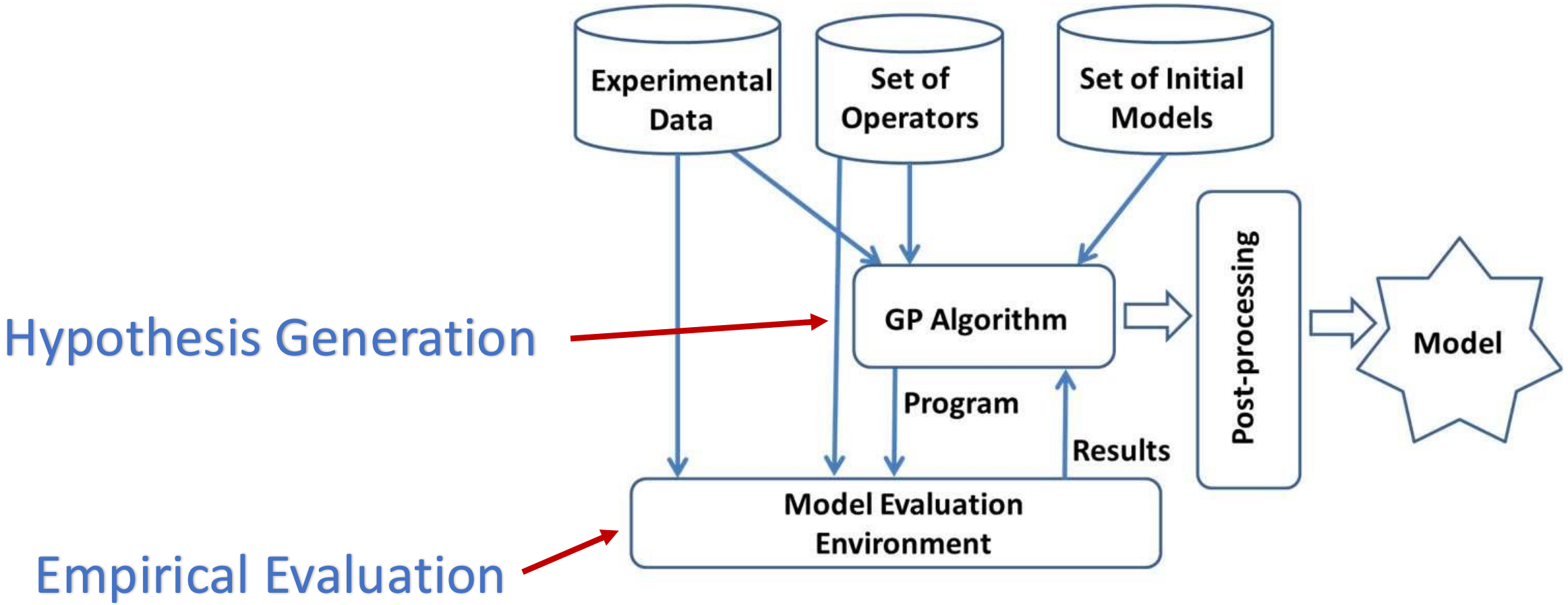
Crossover


Parents
AND
OR
XOR
IN1
OR
IN1
IN3
IN2
IN3
AND
OR
XOR
IN1
IN3
AND
IN3
IN2
IN2
Children
AND
AND
XOR
IN2
IN2
IN1
IN3
AND
OR
XOR
IN1
IN3
OR
IN3
IN1
OR
IN2
IN3

The Key Idea

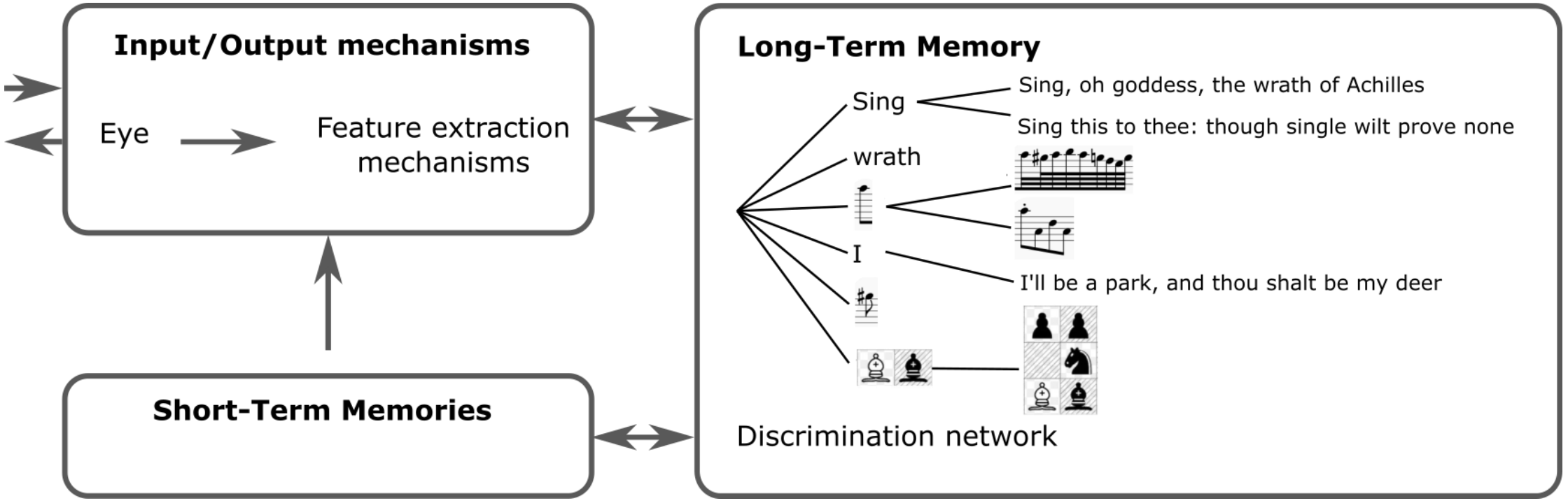
1. A population of theories is (randomly) generated; basic mechanisms are used as building blocks
2. The predictions of the theories in a specific task are compared with the actual empirical data
3. The fitness value of each theory is computed using step 2
4. The best theories are selected for producing the next generation of theories
5. Steps 2 – 4 are repeated until stopping condition is satisfied

Genetically Evolving Models of Science (GEMS)

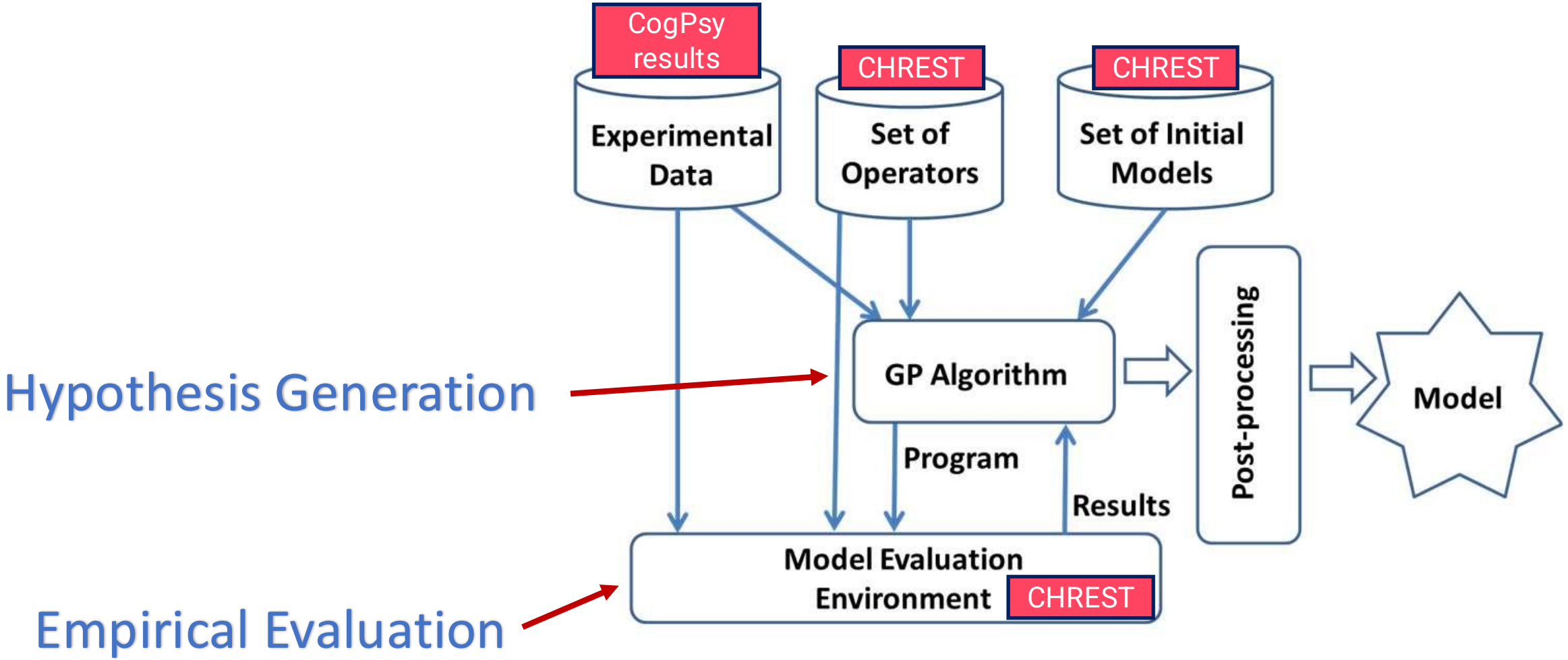


CHREST (Chunking Hierarchy REtrieval STructures)

- Symbolic cognitive architecture
- Focuses on perception
- Learns by chunking
- Psychologically plausible mechanisms
- Cognitive time costs



GEVL = CHREST + GEMS



Verbal Learning

- Nonsense syllable learning
- Humans presented with lists of CVC nonsense syllables
- Trials repeated until learning occurs
- Uncovered laws of memory and learning
- Shares mechanisms with complex tasks

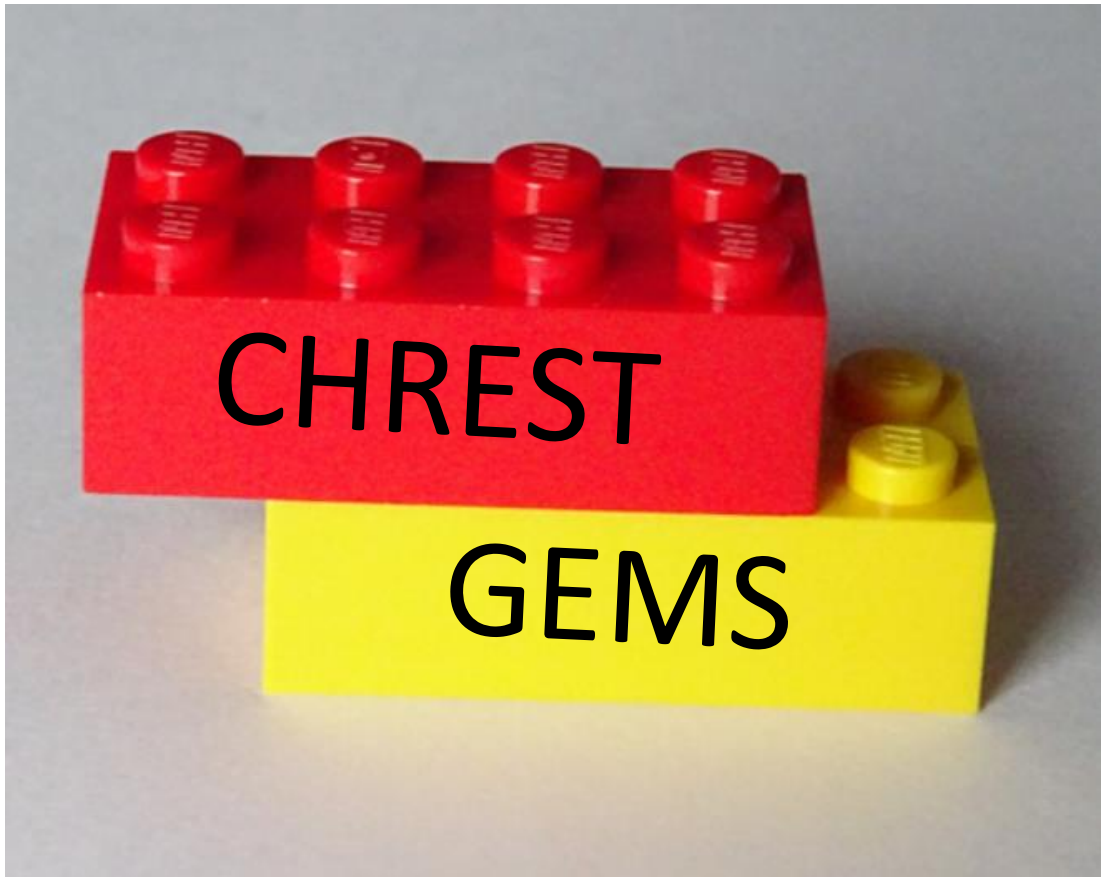
XIL – FOZ
BAZ – YAL

?

GEVL (Genetically Evolving Verbal Learner)

- Combining
  - GEMS
  - CHREST

- Simulations compared with those of EPAM-IV (Richman et al., 2001)
  - Model also based on chunking
  - Originally developed for verbal learning



GEVL Operators

Input

Attend-Stimulus
Attend-Response

LTM and STM

Recognise Stimulus
Recognise-and-learn Stimulus
Recognise-and-learn Response
Learn-and-link

Syntax

Repeat
Respond
Prog

Time

Wait

Pattern Similarity and the Learning Rate

- Nonsense CVC trigrams: XIL, FOZ, YAL, etc.
- 10 S-R pairs (e.g., XIL-FOZ).
- Three similarity conditions: Low, Medium, High.
- Measure learning rate for different conditions:

	SIMILARITY	
Stimuli	**Low**	XIL, TOQ, WEP, DUF, MIZ, JUK, NAS, HOV, BIR, GAC
	Medium	HIZ, VEC, VIR, JUW, HUL, FEC, YOR, JAL, FOZ, YAW
	High	HUX, HEX, YAL, YOR, JIR, YOL, JAX, JIX, JER, HUL
Responses	**Low**	VOD, HAX, CEM, KIR, SIQ, FEP, BAJ, LOZ, TUW, YUG
	Medium	HIZ, VEC, VIR, JUW, HUL, FEC, YOR, JAL, FOZ, YAW
	High	HUX, HEX, YAL, YOR, JIR, YOL, JAX, JIX, JER, HUL

Experiment Procedure (Low-Low condition)

X I L – ? (2 sec)

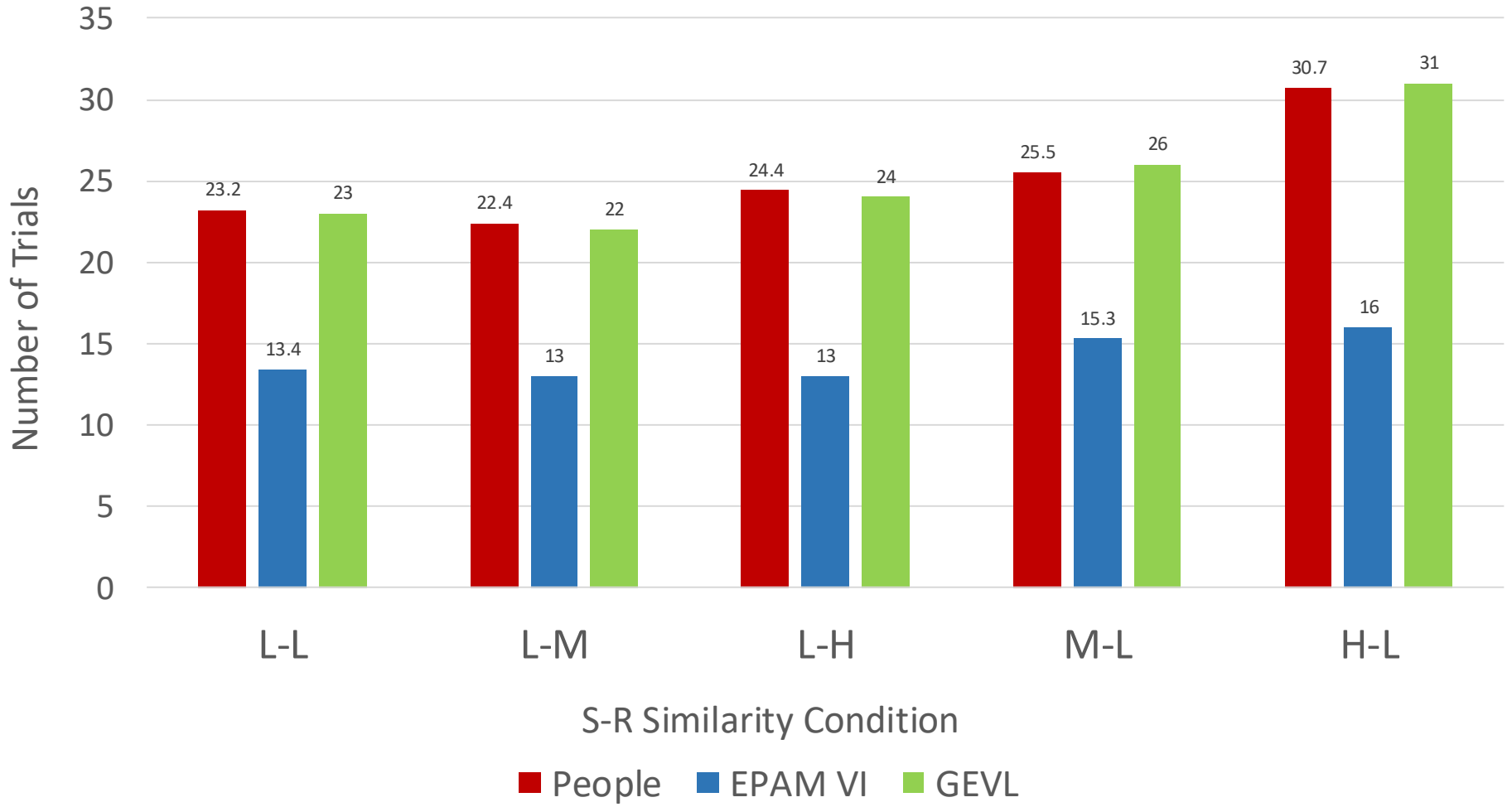
X I L – F O Z (4 sec)

…Repeat for 9 other S-R pairs… (End of Trial 1)

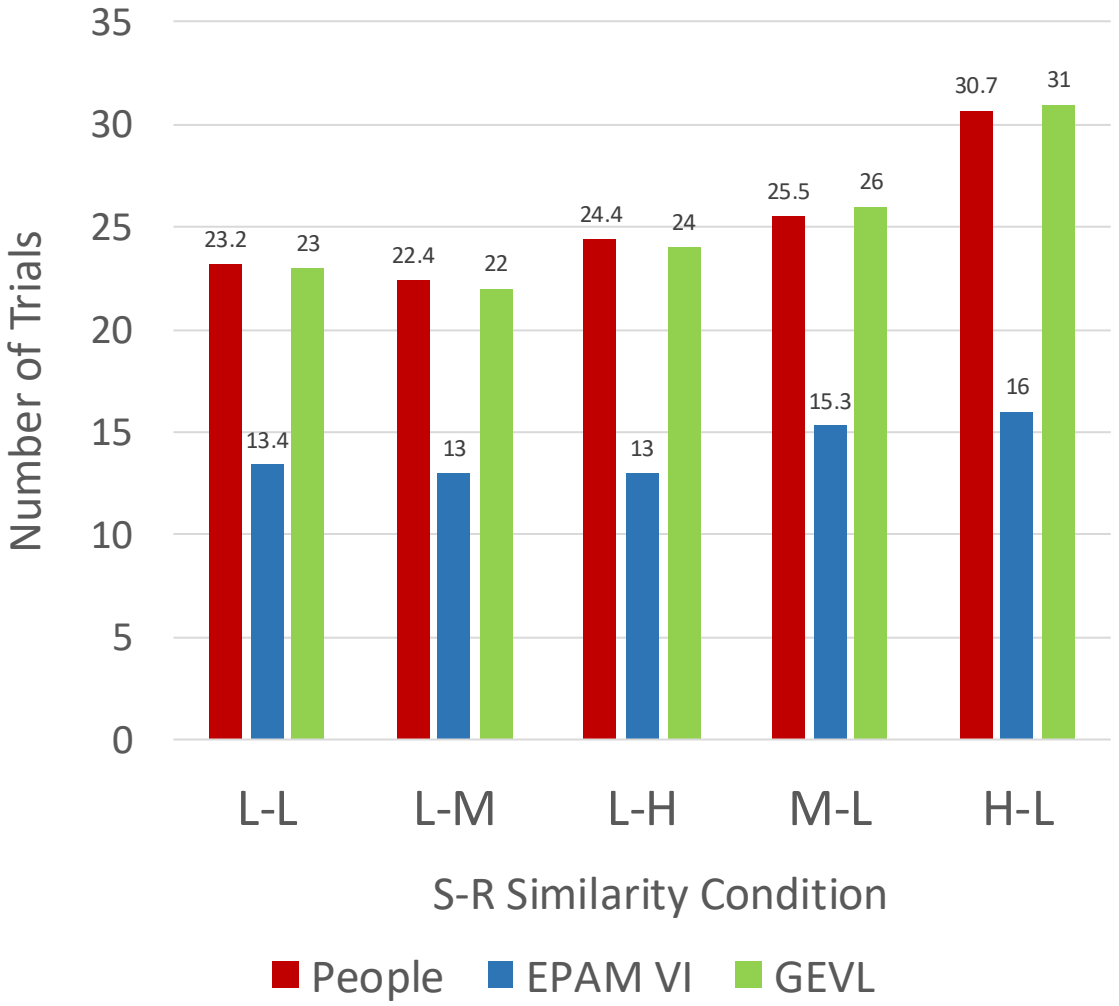
X I L – ? (2 sec)

…Repeat trials until get 10 correct Responses…

The Effect of Pattern Similarity on the Number of Learning Trials (Humans, EPAM VI, GEVL)



The Effect of Pattern Similarity on the Number of Learning Trials (Humans, EPAM VI, GEVL)




```
(PROG4
  (PROG4 (LEARN-AND-LINK)
      (PROG4 (RECOGNISE-ST) (ATTEND-STIMULUS)
            (PROG3 (RESPOND) (ATTEND-RESPONSE)
            (ATTEND-STIMULUS))
              (REC-AND-LEARN-ST))
             (REC-AND-LEARN-ST) (RESPOND))
            (PROG4 (RESPOND) (ATTEND-RESPONSE)
(LEARN-AND-LINK)
             (ATTEND-STIMULUS))
            (WAIT-1000) (REPEAT2 (ATTEND-
RESPONSE) (ATTEND-RESPONSE)))
```

Discussion

- Simulations showed that multiple models account for the data well
  - In line with research on individual differences in psychology
- Models generated by GEMS do much better than EPAM-IV
- Model are not “black boxes”
  - They are readily interpretable
  - Architecture is explicit
  - Sets of cognitive strategies are explicit too
- However, understanding models require some work
- Procedures are developed for generating pseudo-code from GEMS programs

Discussion

- GEMS has mostly simulated simple perceptual and short-term memory tasks
- Linking with CHREST opens up new opportunities
  - Tasks with fairly complex learning
  - CHREST deals with learning
  - GEMS deals with strategies
- Can GEMS evolve
  - Learning mechanisms?
  - CHREST-like architectures?

Thank you!