The Sufficient Feature Model Applied to the Automatization of a Visual and Memory Search Task

By

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Overview of the Presentation

1- Basic findings in the memory and visual search task

2- Overview of the Sufficient Feature Model (SFM)

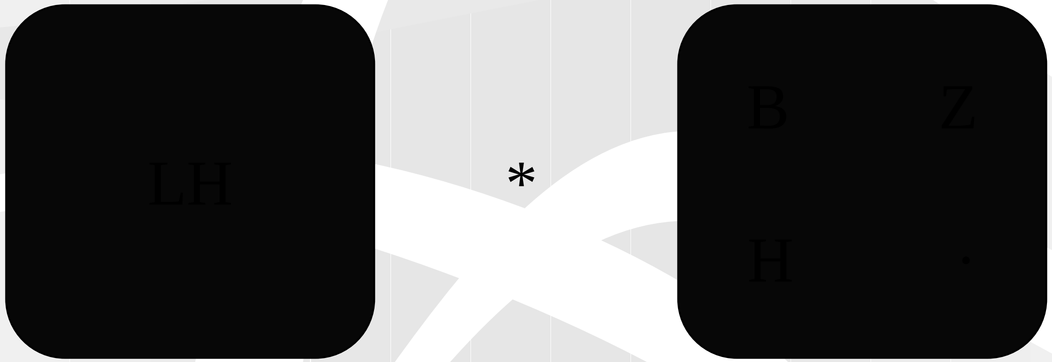
3- Results of a Computer Simulation

4- Further Results

5- Future Direction of Research

1- Basic Findings in the Memory and Visual Search Task

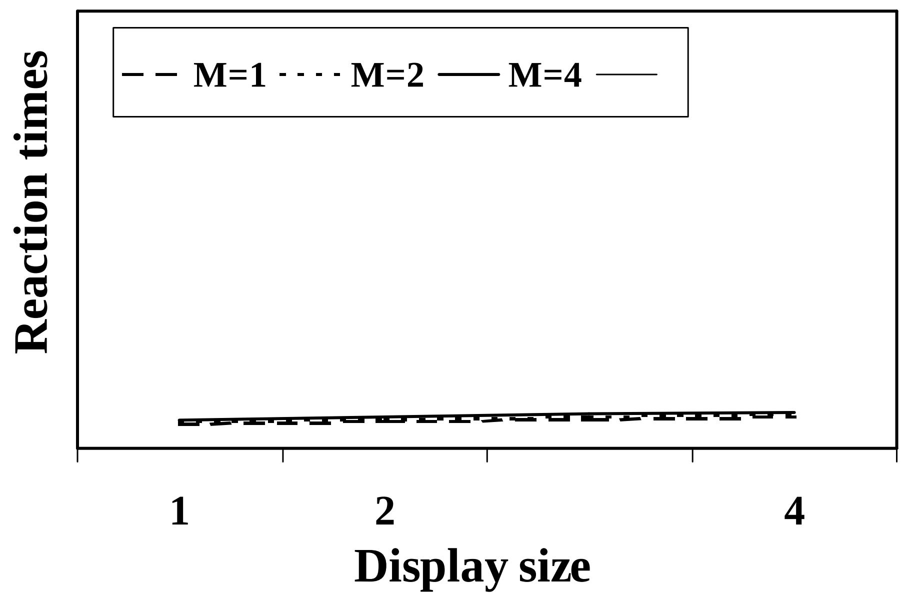
- Two loads are manipulated: Memory load and Display load



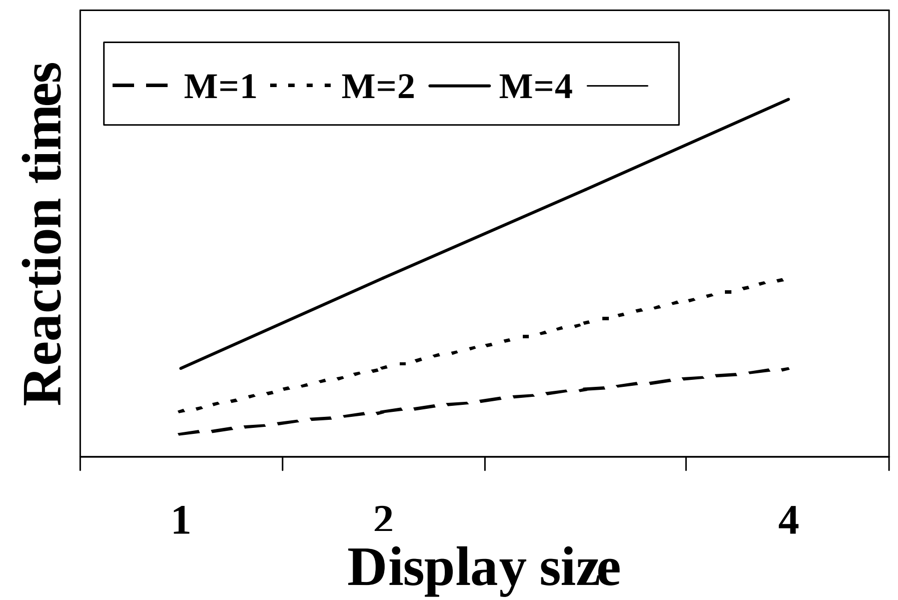
The answer is:
“Present”

- We measure the reaction time; subjects must keep their error rates lower than 5%

- In consistent mapping conditions (CM), the load effect vanishes with practice:



- In varied mapping conditions (VM), the learning is small, the load effect remains large:



2- The Sufficient Feature Model (SFM): Basic Assumptions

The SFM has three basic assumptions:

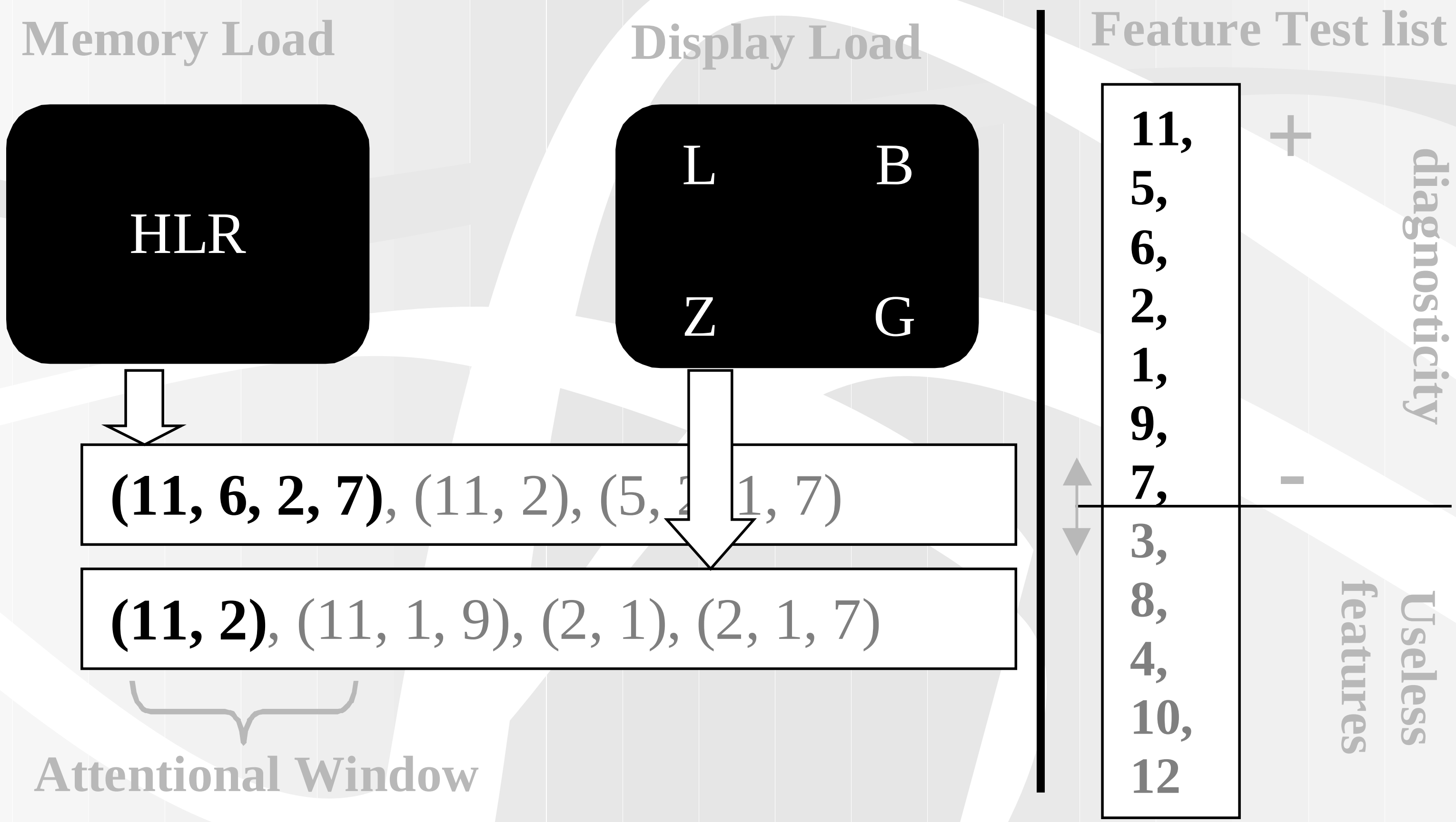
1) comparison mechanism: based on non-atomic representation of stimuli (feature representation)

2) learning mechanism: based on the reduction of information using:

- Ordering of the feature tests based on diagnosticity
- Reducing the number of feature tests performed

3) limited-capacity handling of features (an attentional window)

Diagram of the Decision Mechanism



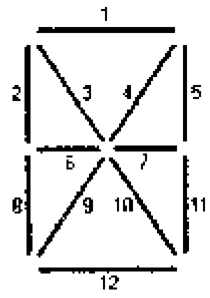
The Sufficient Feature Model (SFM): Parameters

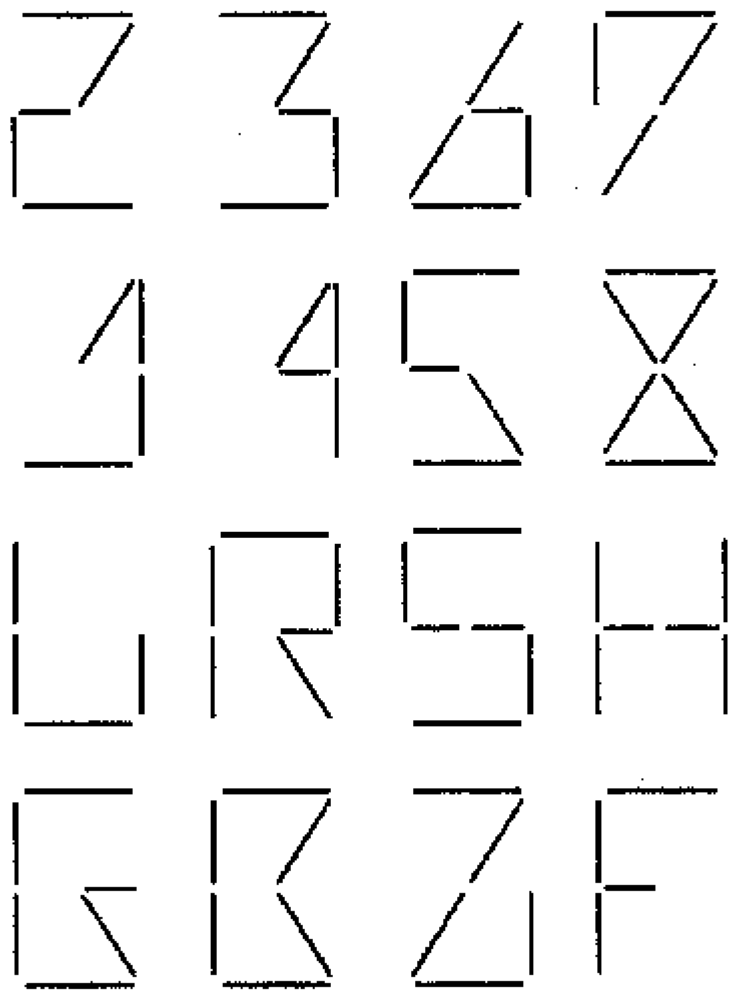
The SFM has three parameters:

- %Error accepted: with 5%, it accepts 1 error out of 20 trials
- Size of the attentional window: it must be large enough to contain the features of the most complex character
- Character composition: we used simplified characters, composed of lines only

Characters Used in the Simulation

- Inspired by McClelland and Rumelhart (1981)
- The character “2” is described by the list (1, 4, 6, 8, 12)





The Sufficient Feature Model (SFM): Computer Simulation

- The SFM has no free numerical parameters
- It measures the number of features that went under the attentional windows
- The simulation is trained by practicing on the same trials as human did
- There is no forgetting in the simulation

3- Behavior of the SFM

Results of the simulation are in this order:

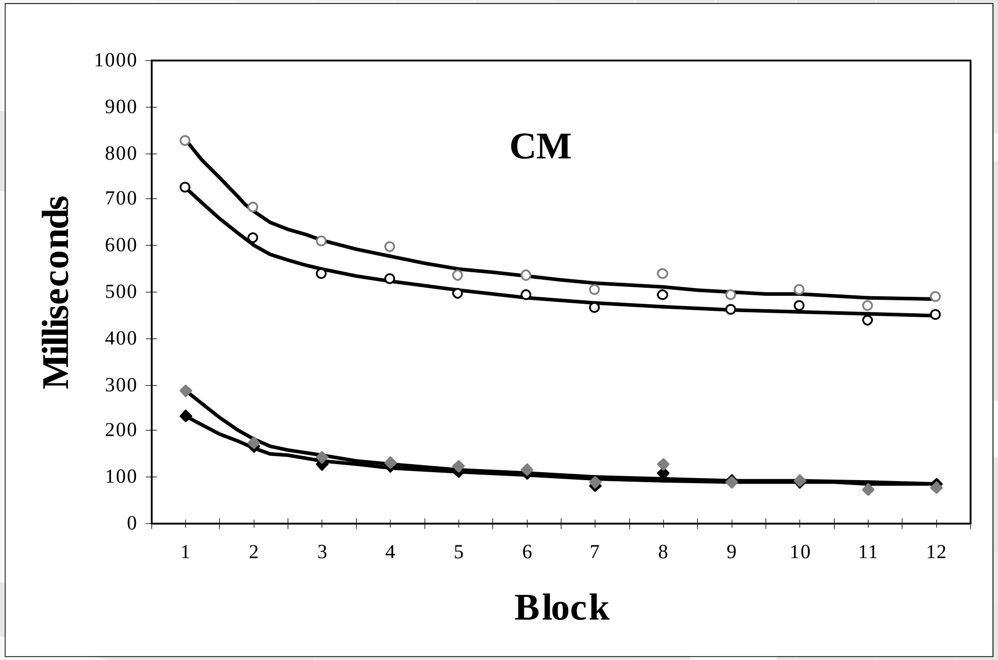
- Learning curves data
- Mean number of features considered
- Standard deviation of the number of features considered

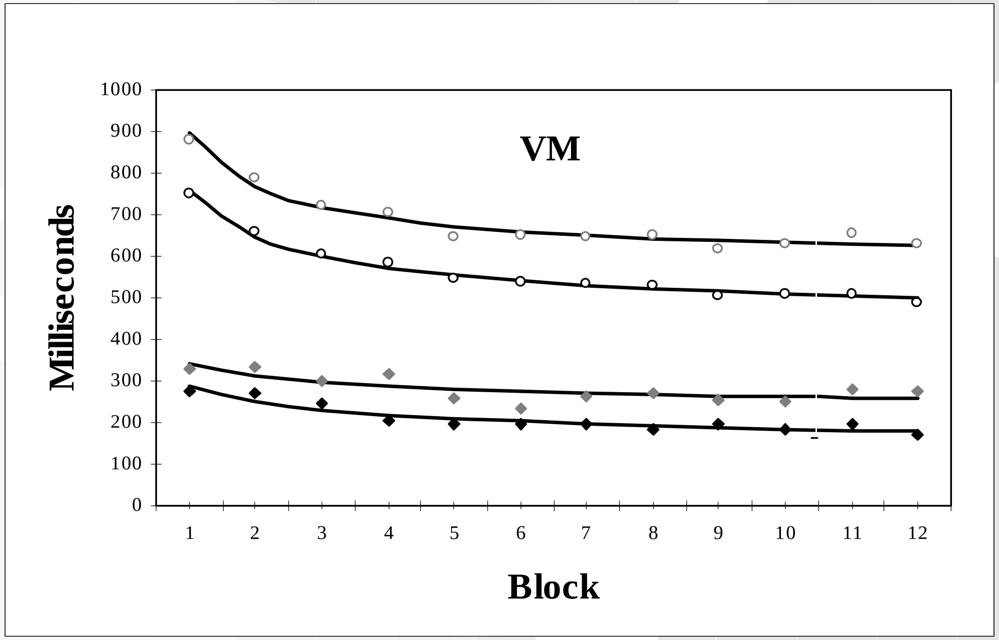
They are compared to two groups of 4 human subjects, one trained for 12 blocks in CM condition, the other trained in VM condition

Learning Curve

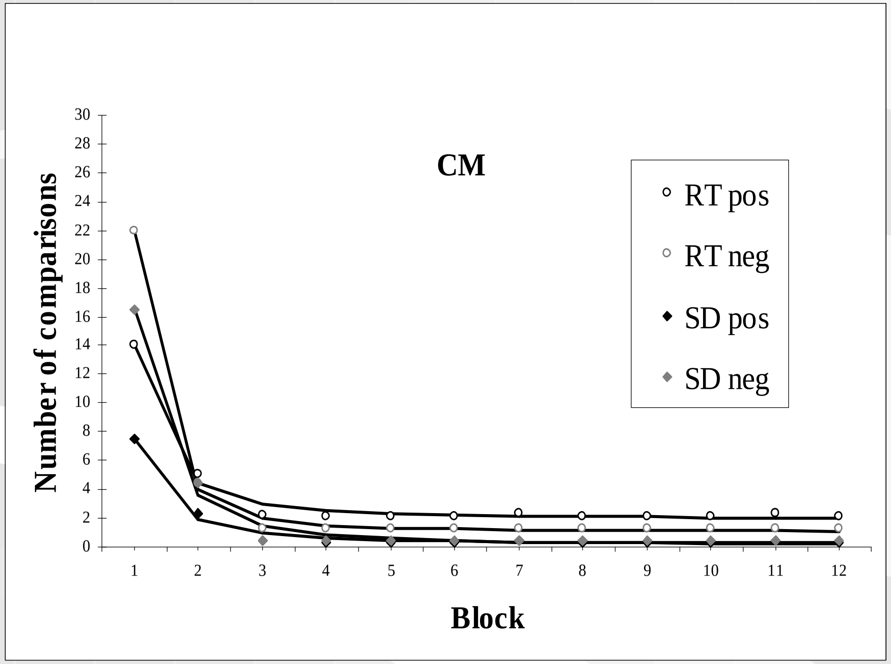
The ordering of the feature tests results in a faster rejection of distractors

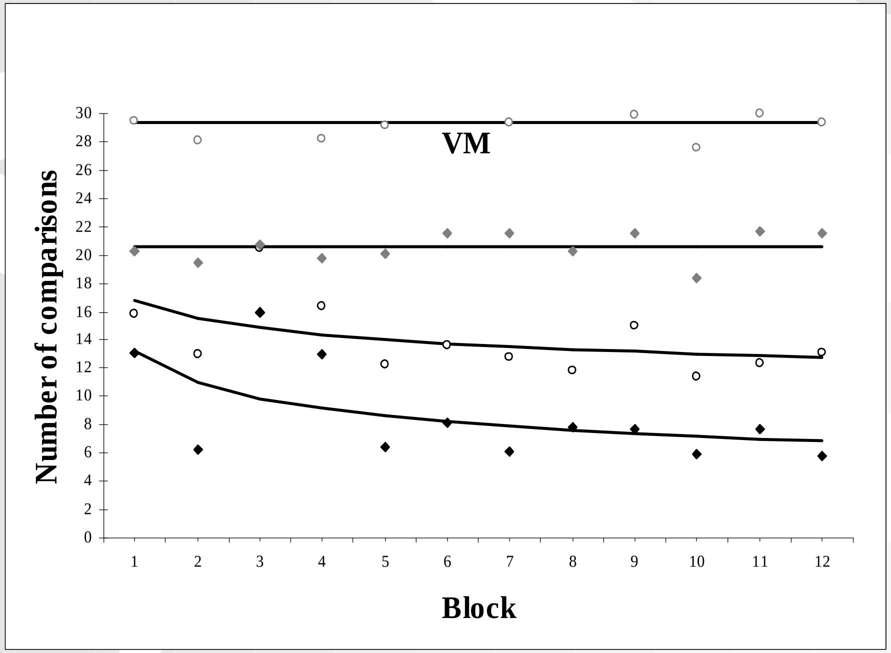
Therefore, there is a visible learning curve both in CM and in VM conditions





Learning rates are equals

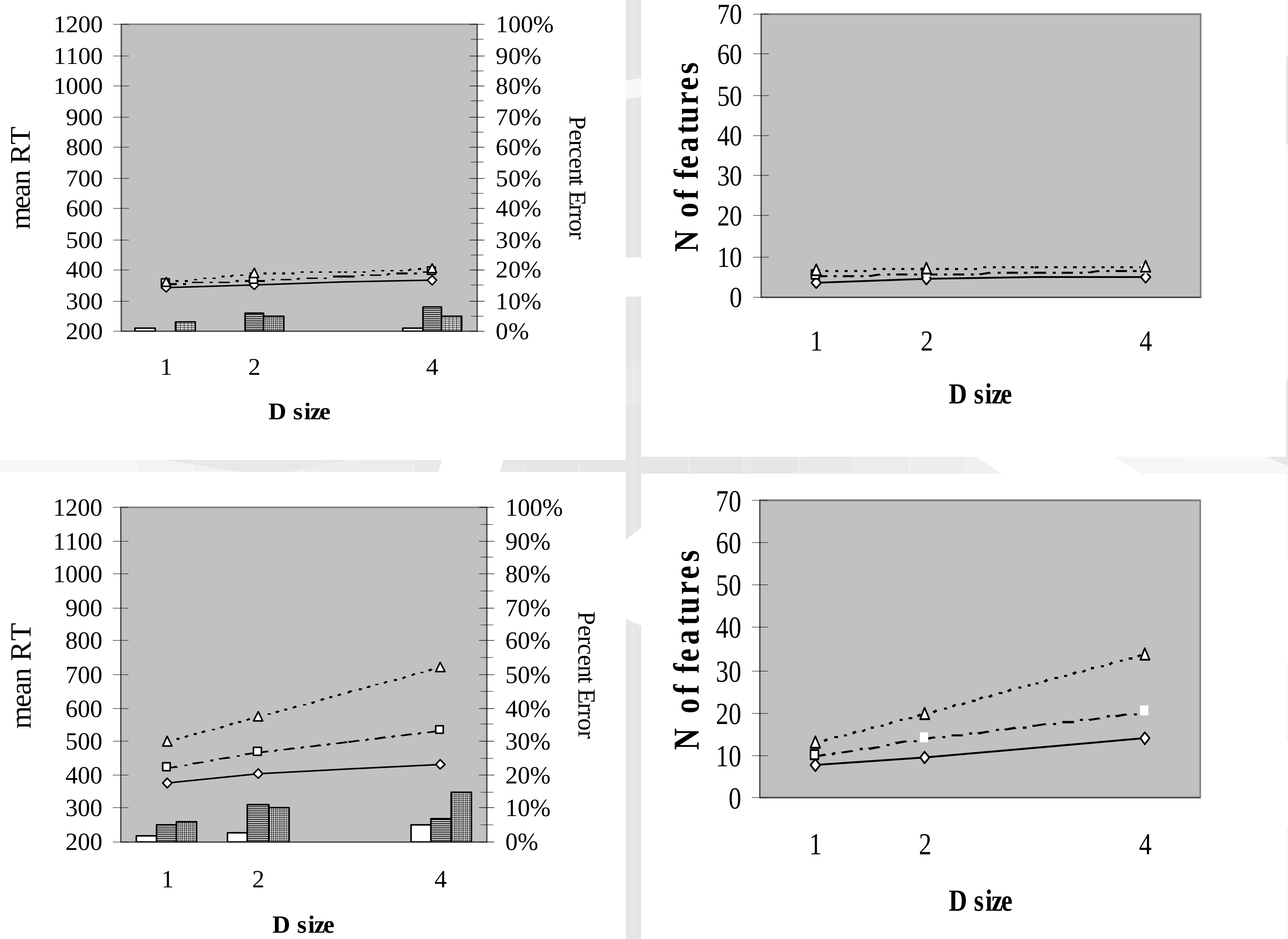




Learning rates are also equals

Mean Reaction Time

- In CM condition, a limited number of features discriminates all targets from distractors. There is no overload of the attentional windows
- In VM condition, the number of features needed remains large. The attentional windows must swap from character to character


mean RT
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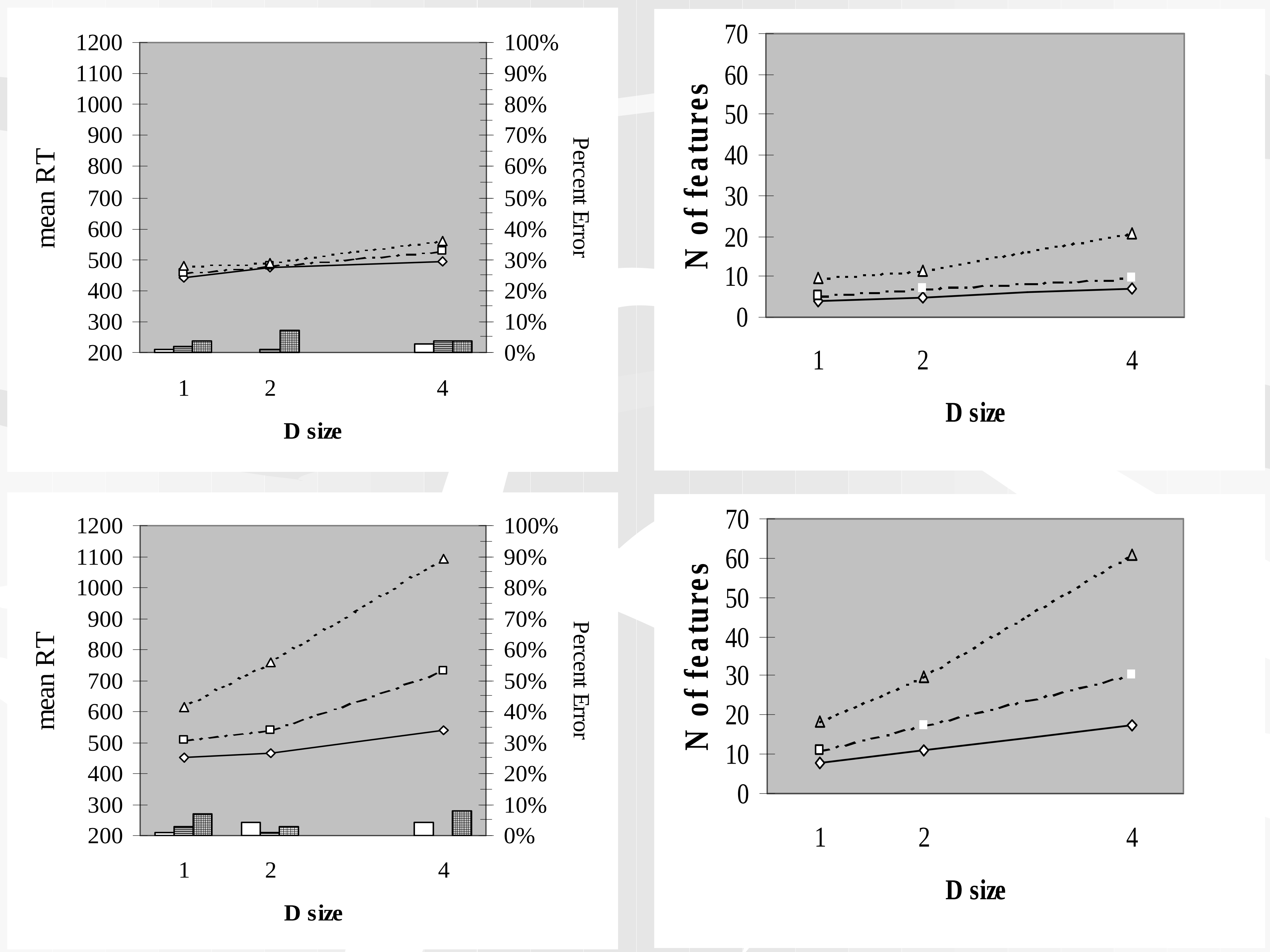

mean RT
Percent Error
D size
N of features
1
2
4

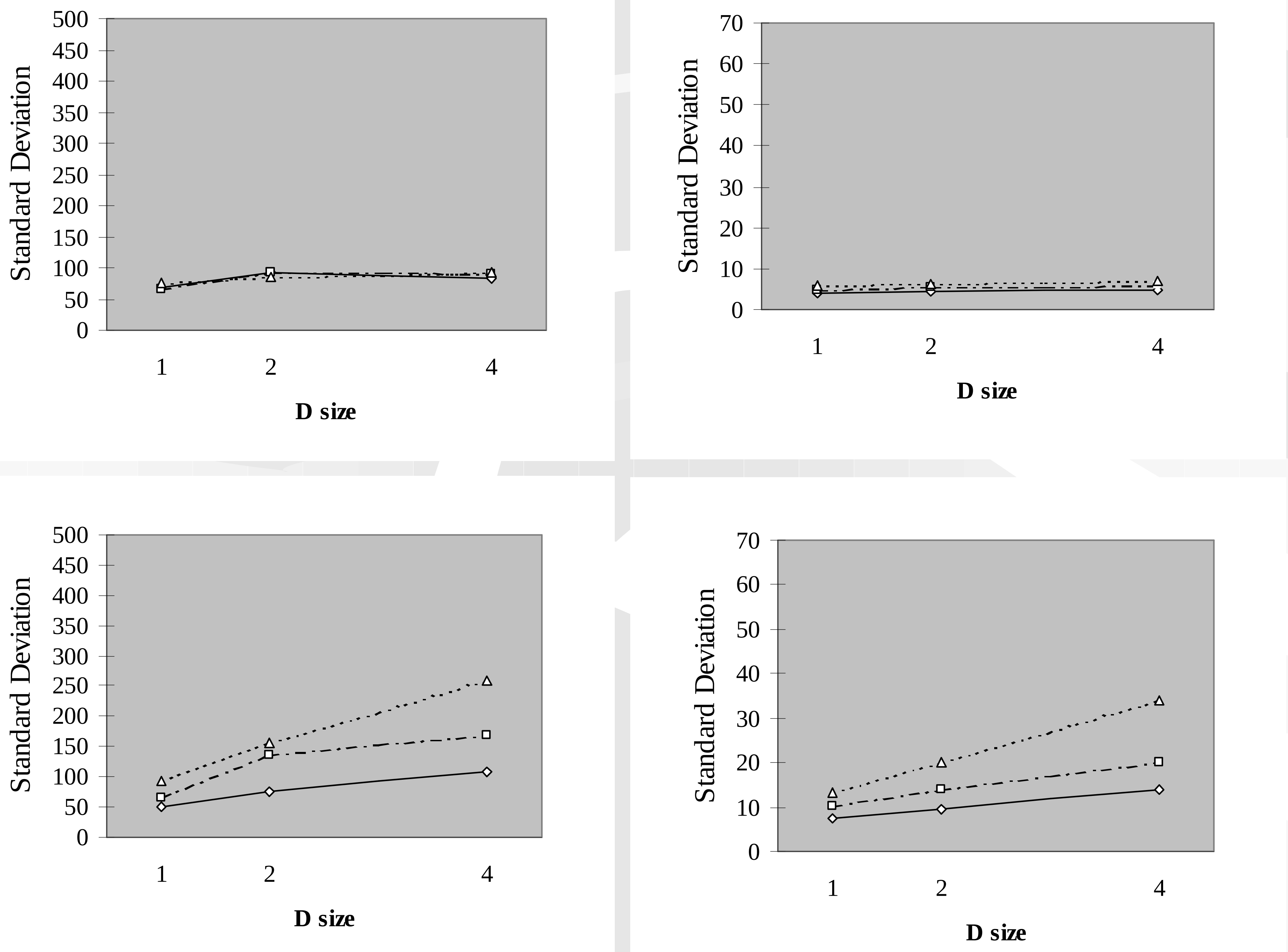
Standard Deviation

In the SFM:

- Negative trials: To be exhaustive on character locations means to be self-terminating on features
- Positive trials: To be self-terminating on character locations means to be exhaustive on features located above diagnostic threshold

Therefore, variance on positive and negative trials should behave in a similar fashion.

It is opposed to a strict serial model, where negative trials should have a smaller variance


Standard Deviation
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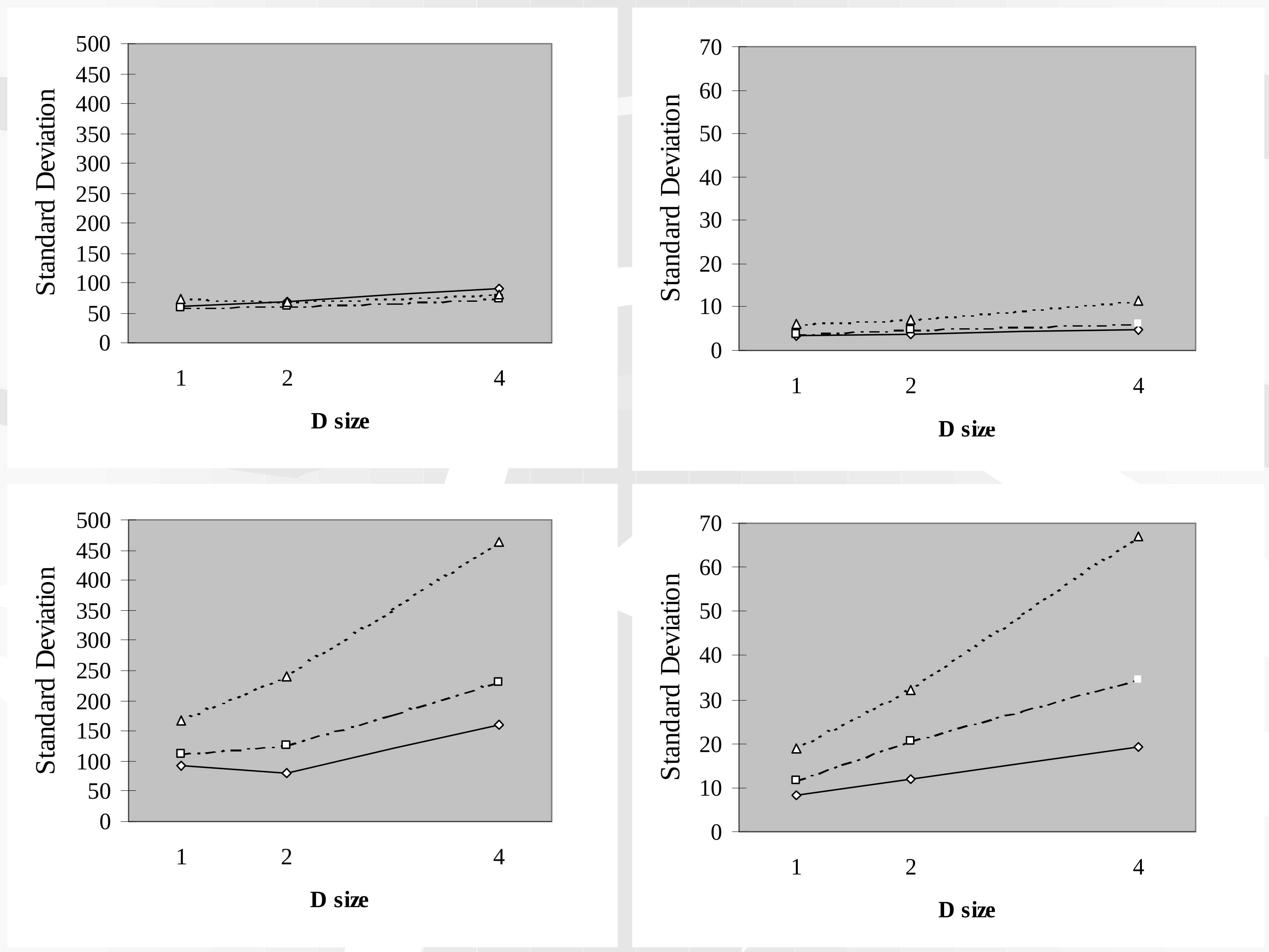

Standard Deviation
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Summary of the Results

A decision process based on reduction of information assumptions reproduces very well the means and standard deviation for both CM and VM conditions.

This is done by:

- evaluating diagnosticity on a trial by trial basis and by
- testing for useless features, based on the % of error allowed.

4- Further Results

A) Categorical Manipulation

In a CM conditions, targets are always the same. They can be seen as a category.

Do pre-established categories alter performance?

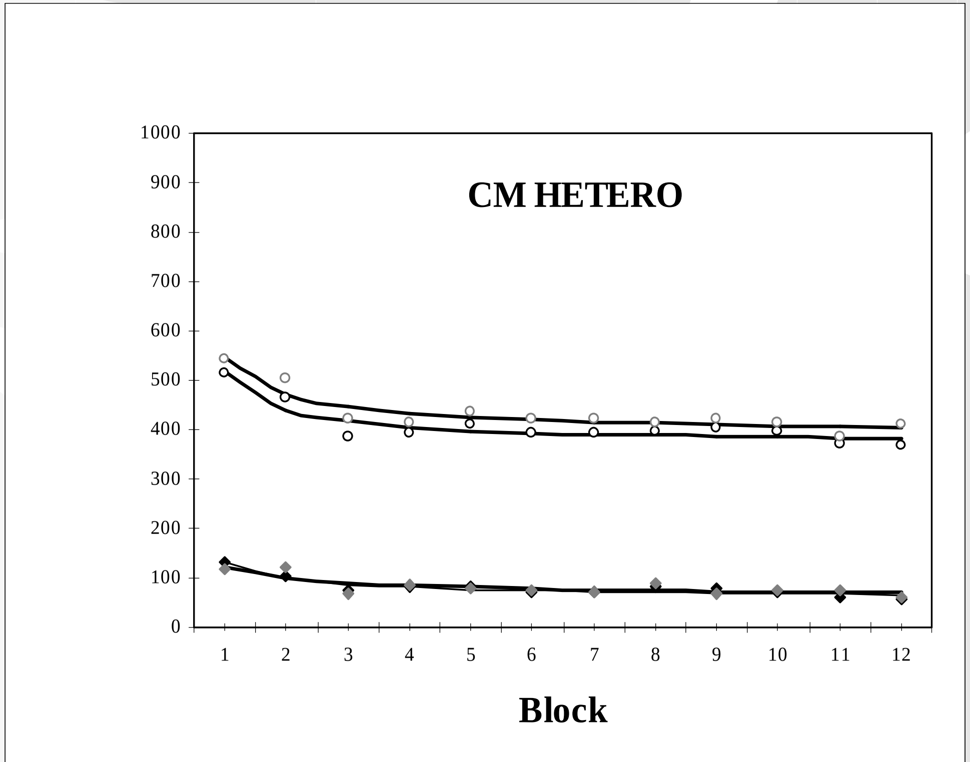
We tested CM conditions with targets and distractors being of the same category of characters (HOMO condition) or of distinct categories (HETERO condition).

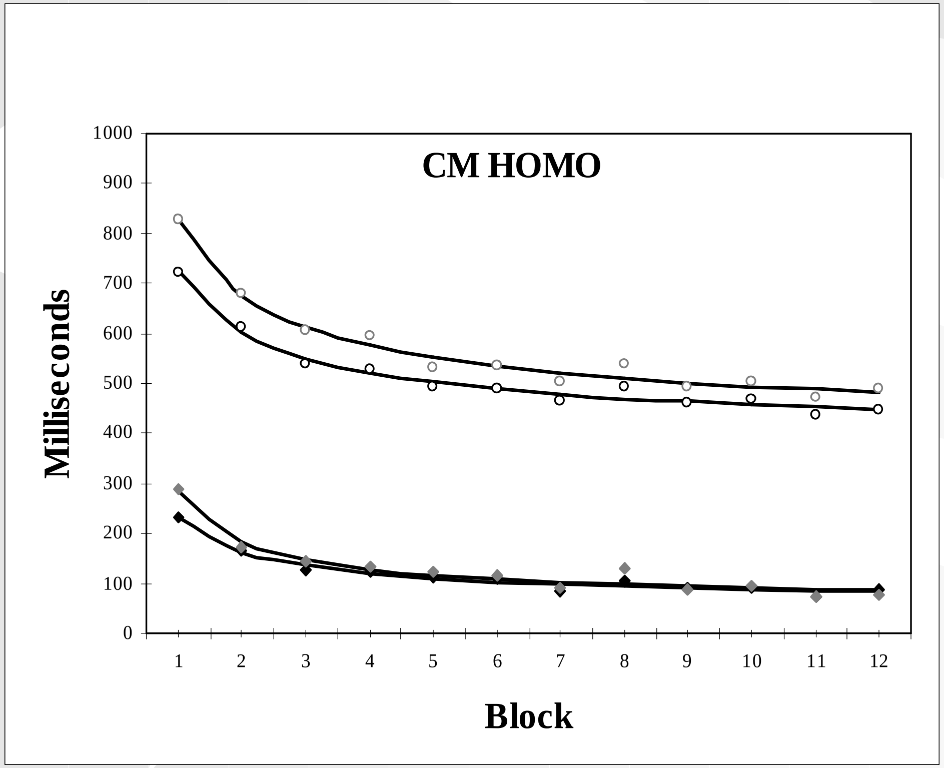
Example of sets	targets / distractors
HOMO	L, H, R, S / Z, B, G, F
vs	
HETERO	2, 3, 6, 7 / Z, B, G, F

CM HETERO group achieve asymptote on the second session of learning.

They show no load effect on the first block

CM HOMO never equals CM HETERO with more than 5000 trials of practice.





With CM learning, a generic representation (GR) composed of diagnostic features of a category might become easier to retrieve than representation of a single target (T).

T $\longrightarrow$ **GR** $\longrightarrow$ Decision $\longleftarrow$ **Test Probe**

This raises the possibility that, after such an association is learned, it might be possible to performed well under Inconsistent Mapping (IM) conditions.

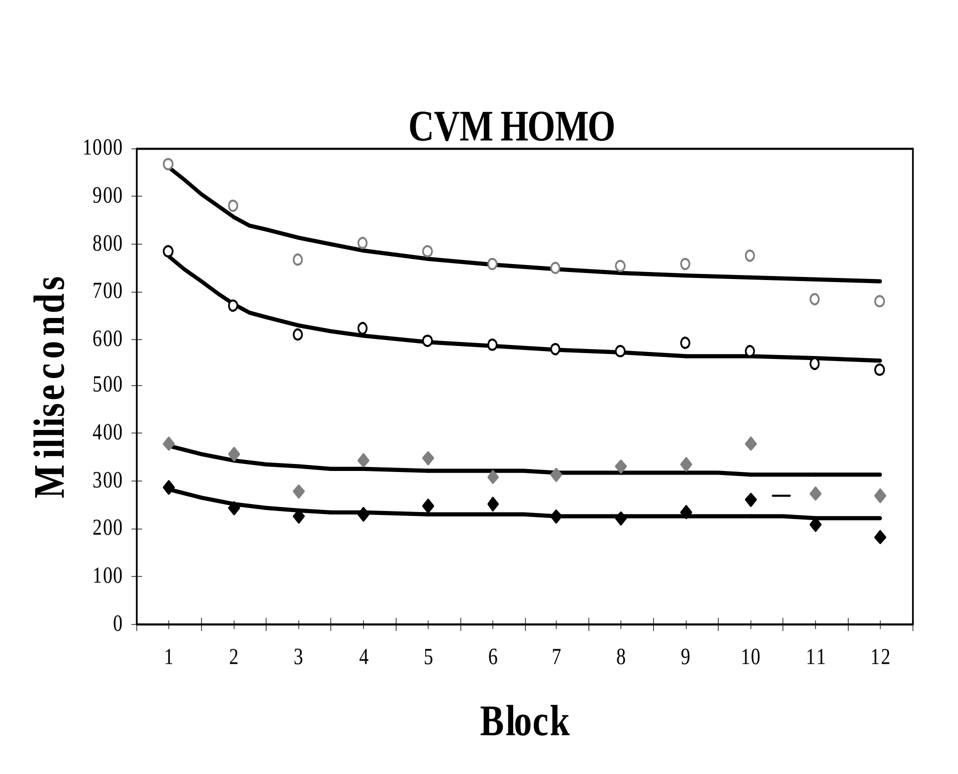
One type of IM is seen next.

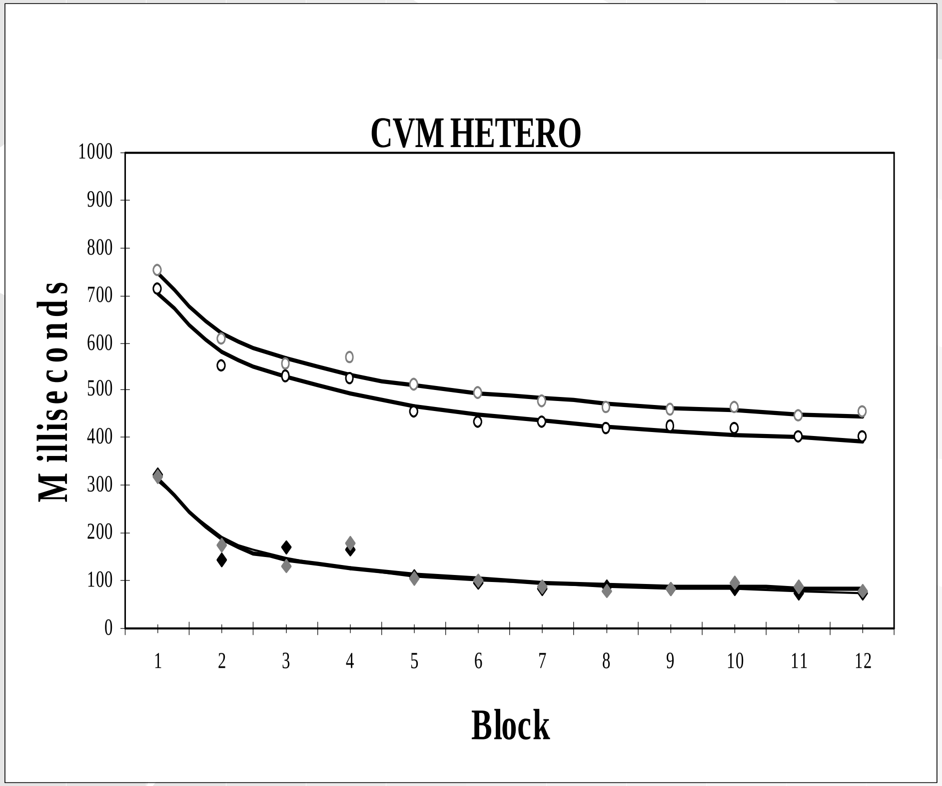
B) Categorical Varied Mapping (CVM) conditions

If GR is easy to retrieve, it might be possible for subjects to alternate between two distinct and mutually exclusive sets of targets and distractors

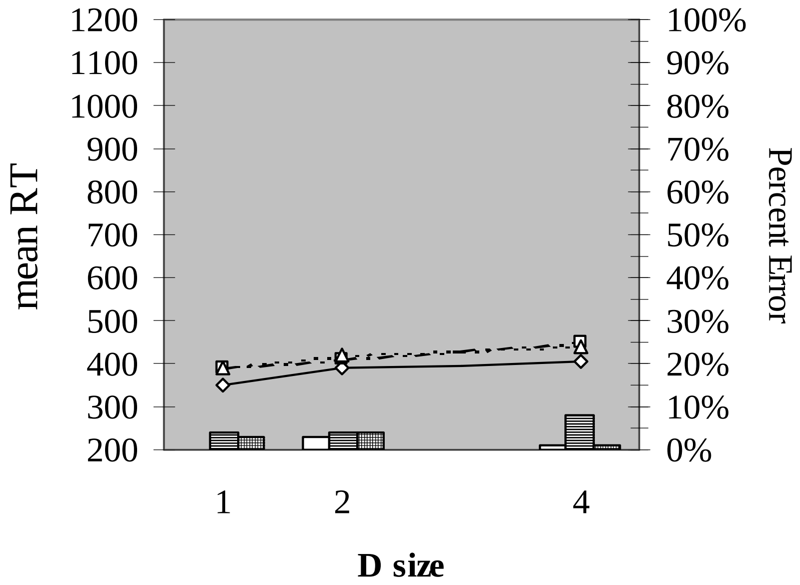
Example of sets	targets / distractors
HOMO	L, H, R, S / Z, B, G, F and
	Z, B, G, F / L, H, R, S
HETERO	2, 3, 6, 7 / Z, B, G, F and
	Z, B, G, F / 2, 3, 6, 7

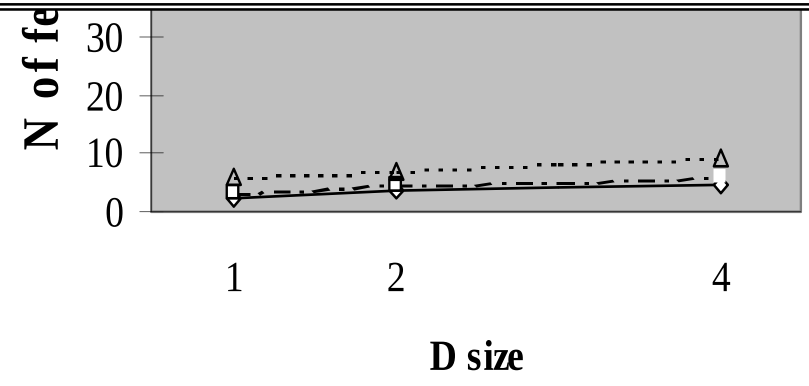
- CVM HETERO results are comparable to CM results (learning curve and load effect)
- CVM HOMO results show learning curve similar to VM groups and large load effect.

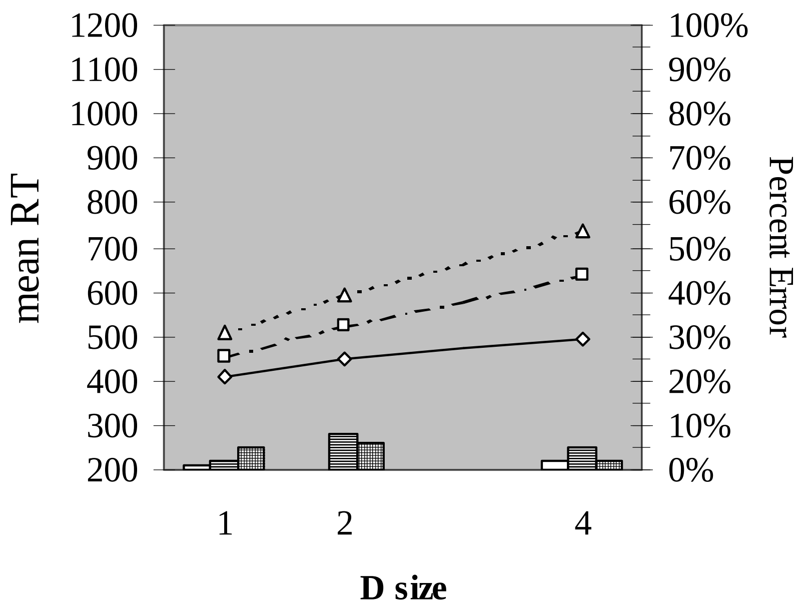


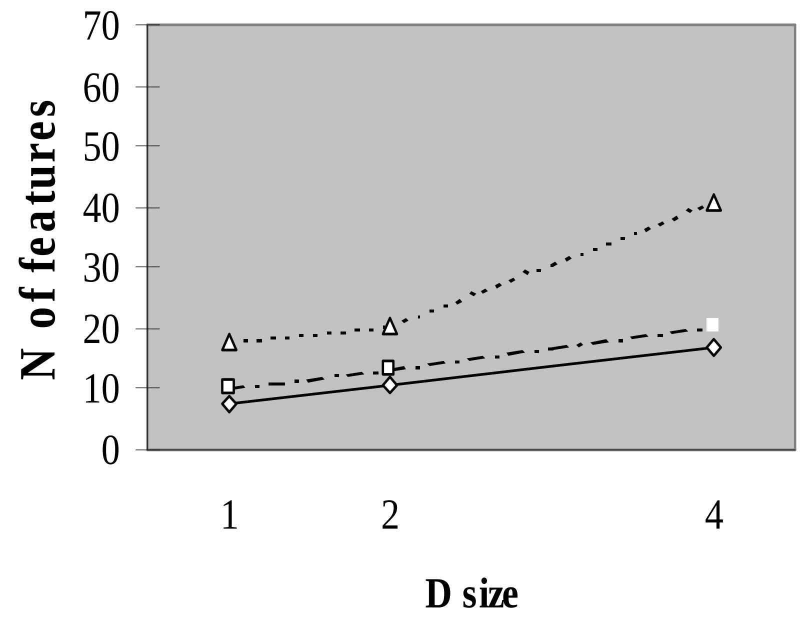


Model was given two feature tests lists to learn from, one for letters, one for digits









Implication of the SFM to Other Theories

A) Category knowledge: With a sensitivity to sets presented, the model can learn in the inconsistent CVM HETERO condition

This is against any direct-access theory of performance (Logan's Instance-based theory of automaticity for instance)

B) Non-atomic representation: Physical similarity effects (such as Distractor-Distractor homogeneity effect and Target-Distractor heterogeneity effect) are easily explained by the SFM.

Furthermore:

With feature representation, standard deviation are well-described.

C) Reduction of information: It captures the essential aspects of CM and VM learning (load effect in both M and SD, some aspects of the learning curves)

5- Future Direction of Research: An a priori test of the SFM

The CM Character and VM Feature task
(Work in progress with C. Lefebvre)

Since characters have two levels of representation (holistic, featural), inconsistencies in mapping is possible: targets / distractors

p d h u / b q n ɥ

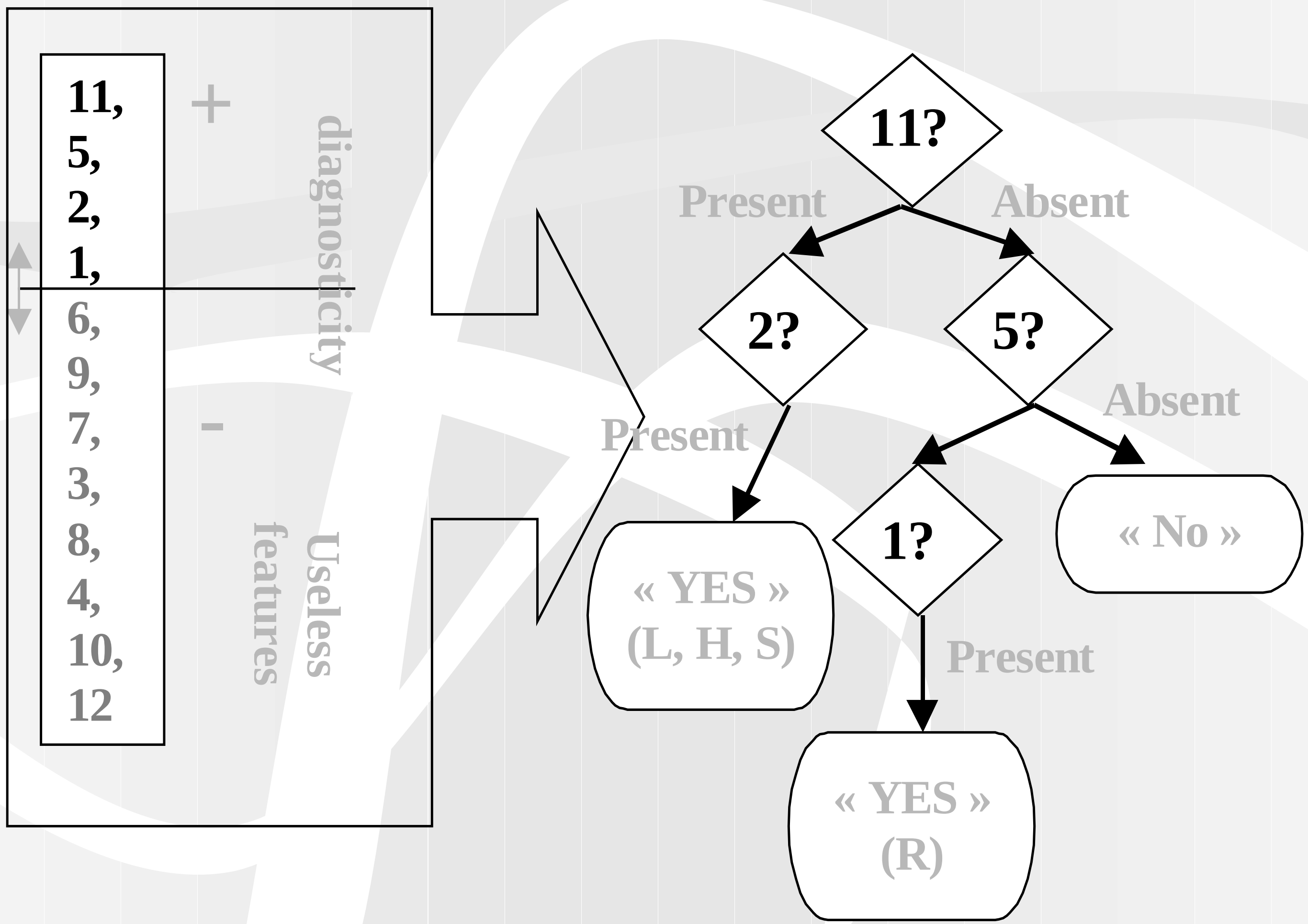
vs

p d b q / h u n ɥ

Will performance be more like VM or CM?

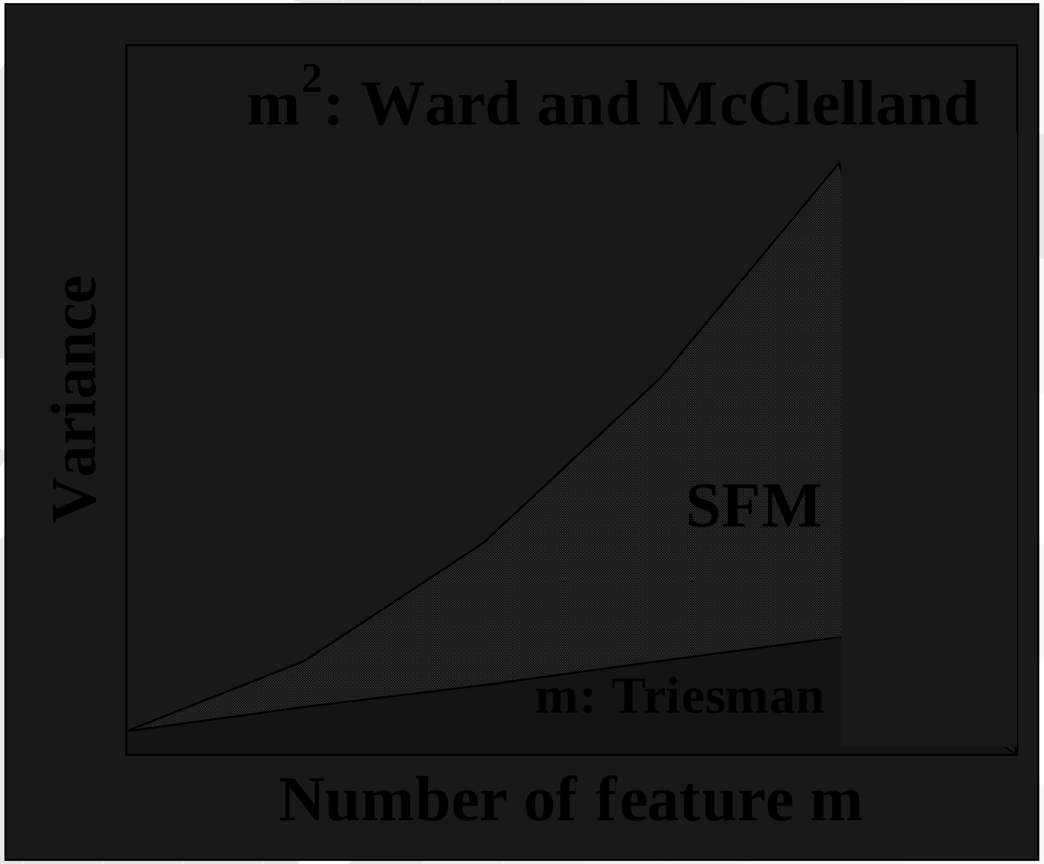
Thank you for your attention.

The GR can be seen as a decision tree where features are nodes, and tests are vertices.



$$Var(1,n) = E(\mathbf{m})Var(\mathbf{T}) + Var(\mathbf{m})E^2(\mathbf{T})$$

- Treisman reports linear variance;
- Ward and McClelland report linear STD;
- Cousineau and Larochelle find in-between results.
- SFM accepts a broad range of value



Some Dimensions in Modeling the Memory/Visual Search Task

- Direct Access (e.g. memory-based)

  vs

  Indirect Access (e.g. GR)

- Single Step (e.g. retrieval of the resp.)

  vs

  Multiple Step (scanning of the display)

- Atomic Representation (features)

  vs

  Holistic Representation (templates)