Faculté des Lettres,
des Sciences Humaines, des Arts,
et des Sciences de l'Éducation

What can schools, teachers and learners learn from implicit learning research?

Fourth scientific symposium of the Association for Research in Neuroeducation, Université de Caen
Caen, Basse-Normandie, France - 27th mai 2014

Robert A.P. REUTER
Institute for Applied Educational Sciences
Research Unit on Education, Culture, Cognition and Society

UNIVERSITÉ DU LUXEMBOURG

my background

Université libre de Bruxelles: Cognitive Psychology
Université du Luxembourg: (Applied) Educational Sciences - Educational Technology

this talk

some "old" facts

and a lot of tentative speculations

"I've heard you're doing research on implicit learning…

so you can teach me how to prepare for my next exam, without me having to study really hard?"

Faculté des Lettres,
des Sciences Humaines, des Arts,
et des Sciences de l'Éducation

Guiding Questions

- What is "implicit learning" (IL)?
- What do we know about IL?
- What are the differences and similarities between IL and explicit learning (EL)?
- In how far could IL be relevant for "school-based learning"?
- What can we learn from IL research to better understand "school-based learning"?
- What could IL-informed teaching scenarios look like?

Defining IL

Term first coined by Reber (1967): "The process by which knowledge about the rule-governed complexities of the stimulus environment are acquired independently of conscious attempts to do so."

In other words, a situation where knowledge of co-variations in the environment is acquired **without** explicit **intention** of learning, **without awareness** of the learning process and **without knowledge** of what has been learned

Vaguely synonymous with incidental learning and unconscious learning

Does that really exist?

Evidence for IL

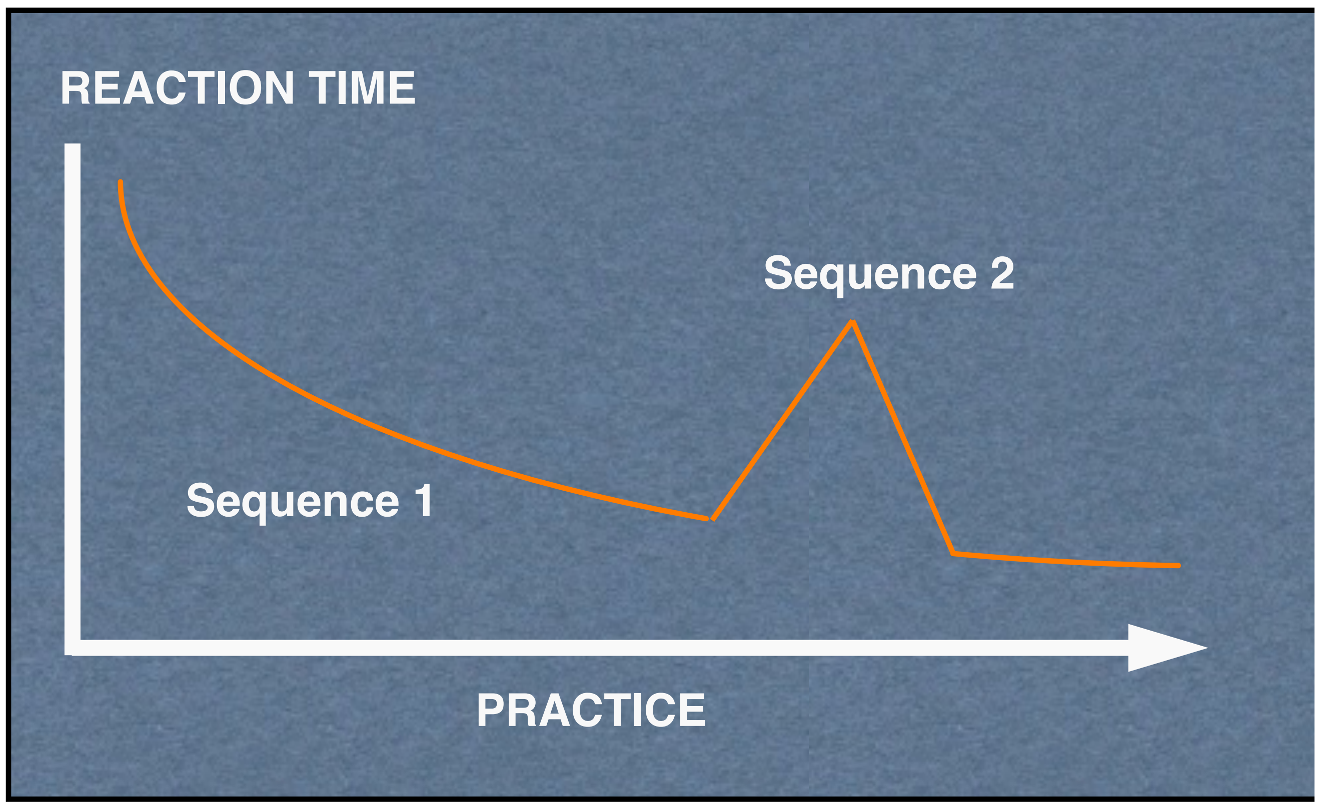
- Artificial grammar learning (Reber, 1967)
- Sequence learning (Nissen & Bullemer, 1987)
- Dynamic system control (Berry and Broadbent, 1984)
- Contextual cueing (Chun & Jiang, 1998)
- Stereotypes and interpersonal biases (Greenwald & Banaji,1995)
- Language learning (Pacton, Perruchet, Fayol & Cleeremans, 2001): Implicit Learning out of the lab: The Case of Orthographic Regularities

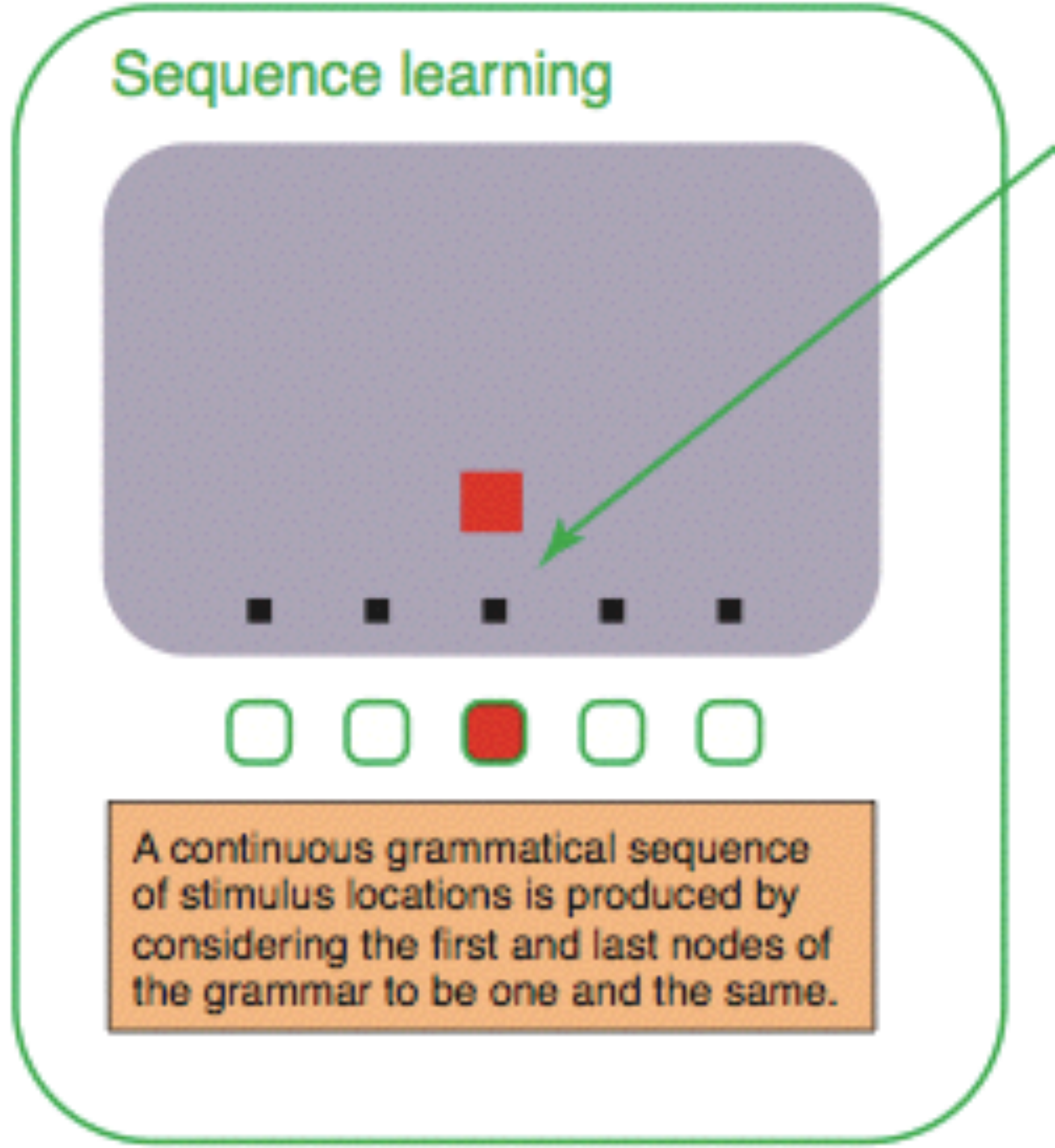
Evidence for IL

- **Artificial grammar learning (Reber, 1967)**
  - asked to memorize a set of letter strings generated by a finite-state grammar
  - AFTERWARDS, told that the strings follow the rules of a grammar
  - asked to classify new strings as grammatical or not
  - classification task better than chance, despite unable to describe the rules of the grammar in verbal reports.
  - **thus we observe a dissociation between classification performance and verbal report**

Evidence for IL

- **Sequence learning**
  deterministic sequence

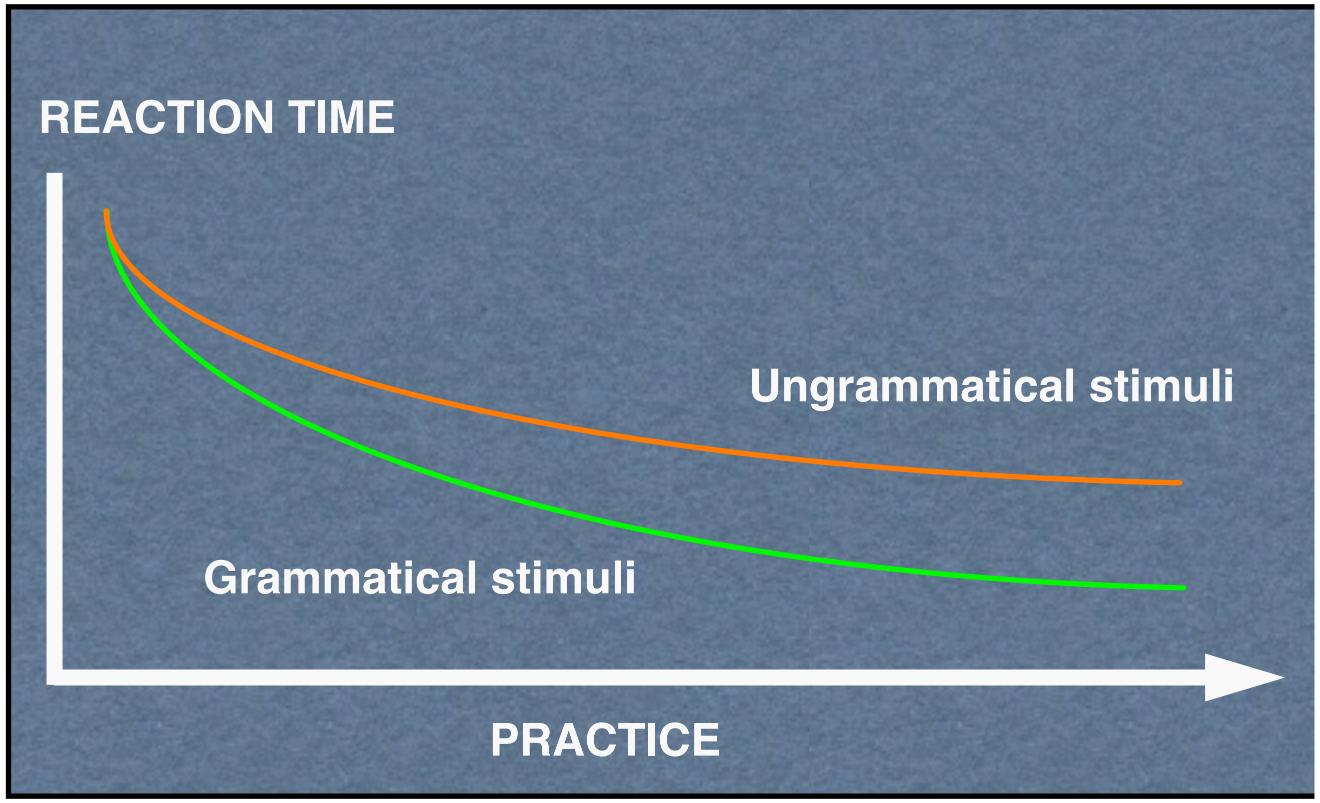


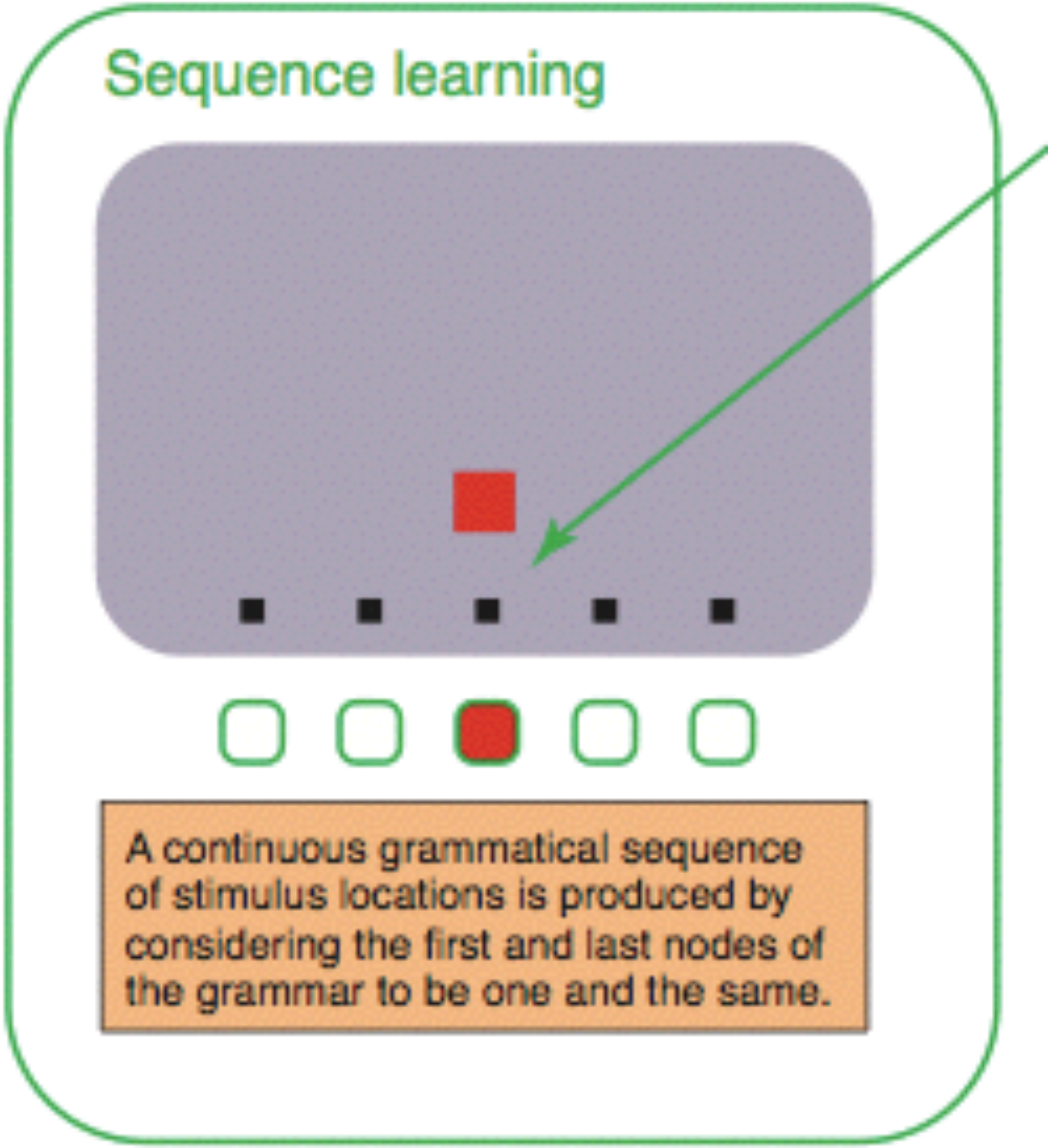


(Cleeremans et al., 1998)

Evidence for IL

- **Sequence learning**
  probabilistic sequence





(Cleeremans et al., 1998)

Evidence for IL

- **Contextual cueing:** a certain information contained in a (visual) scene cues/guides (visual) attention towards a "meaningful" part of the (visual) scene
- Interesting interaction between IL and (visual) consciousness: "IL tells our attention what to become aware of, by using information that we (mostly) remain unaware of."

Expérience standard

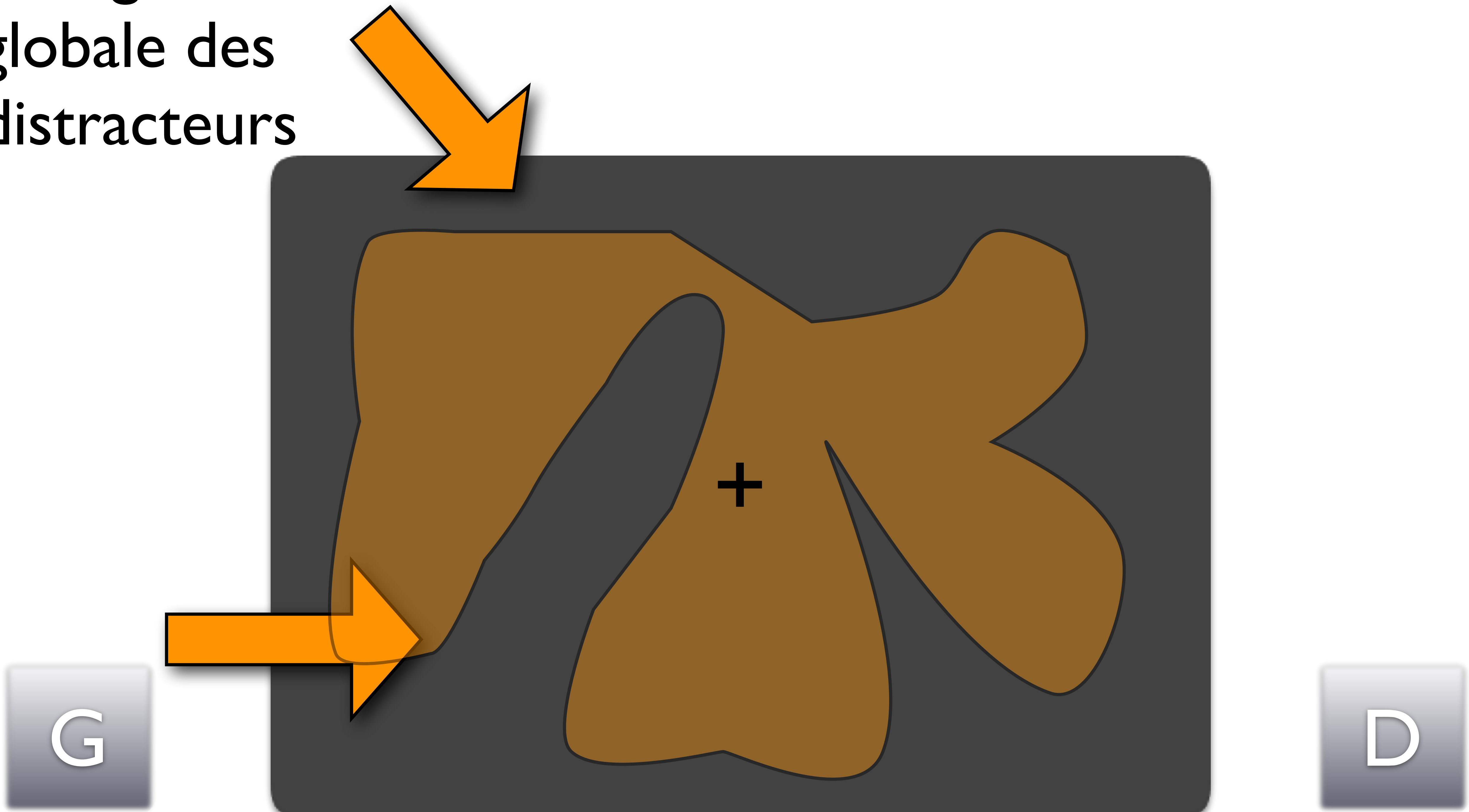
- Tâche: "Nous faisons une étude sur l'attention visuelle" Chercher une cible parmi des distracteurs et indiquer au plus vite son orientation (à l'aide d'une de deux clés)
- Le contexte est défini par la configuration globale des distracteurs.
- Les distracteurs sont assez similaires à la cible (tâche de recherche serielle)
- Nombre equivalent d'essais "gauche" et "droite"

Expérience standard

- A l'insu des participants on présente des essais **prédictifs** et des essais **aléatoires**
- 24 emplacements pour la cible
  - 12 emplacements avec contextes aléatoires
  - 12 emplacements avec contextes répétés
- 30 blocks de 24 essais chacun
- Les temps de réaction sont enregistrés

Contexte: configuration globale des distracteurs

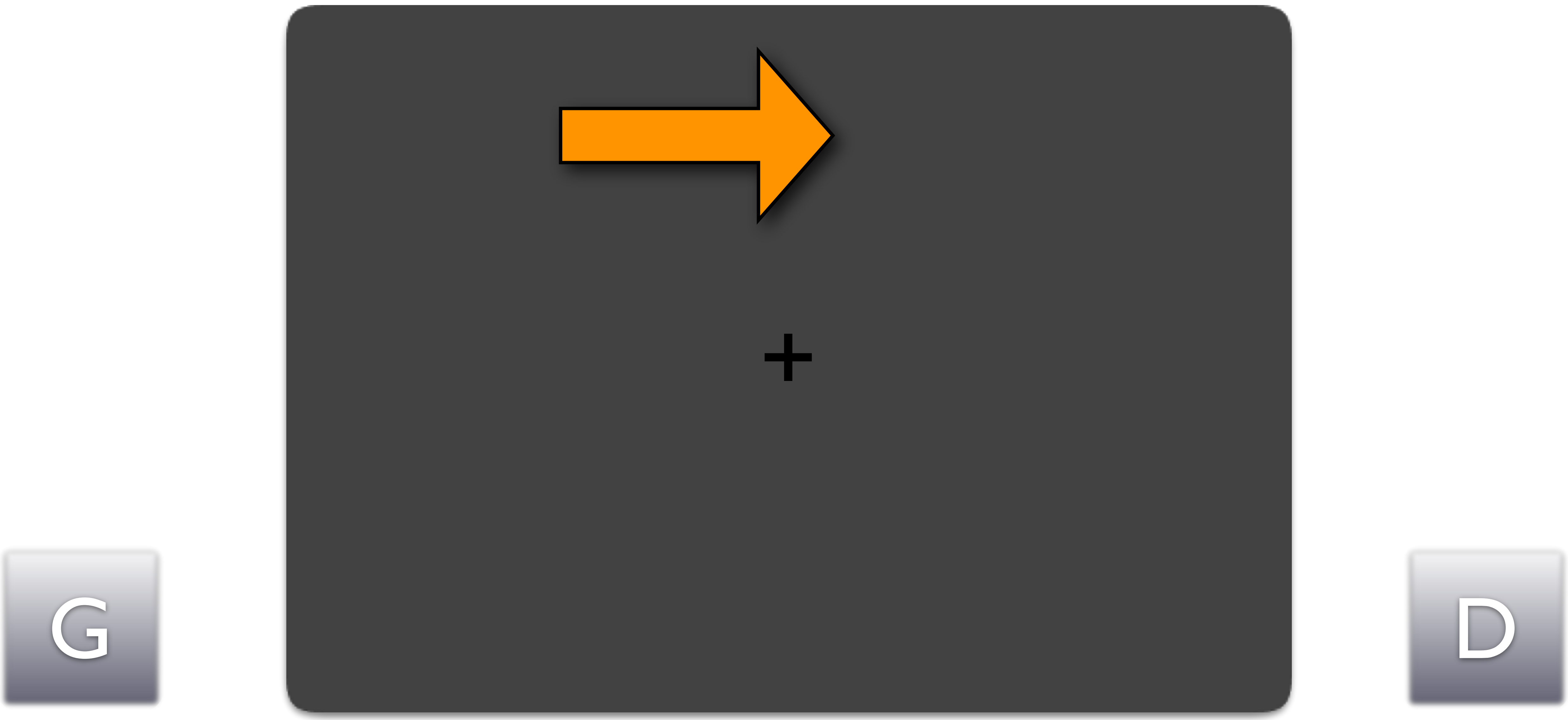
Démonstration



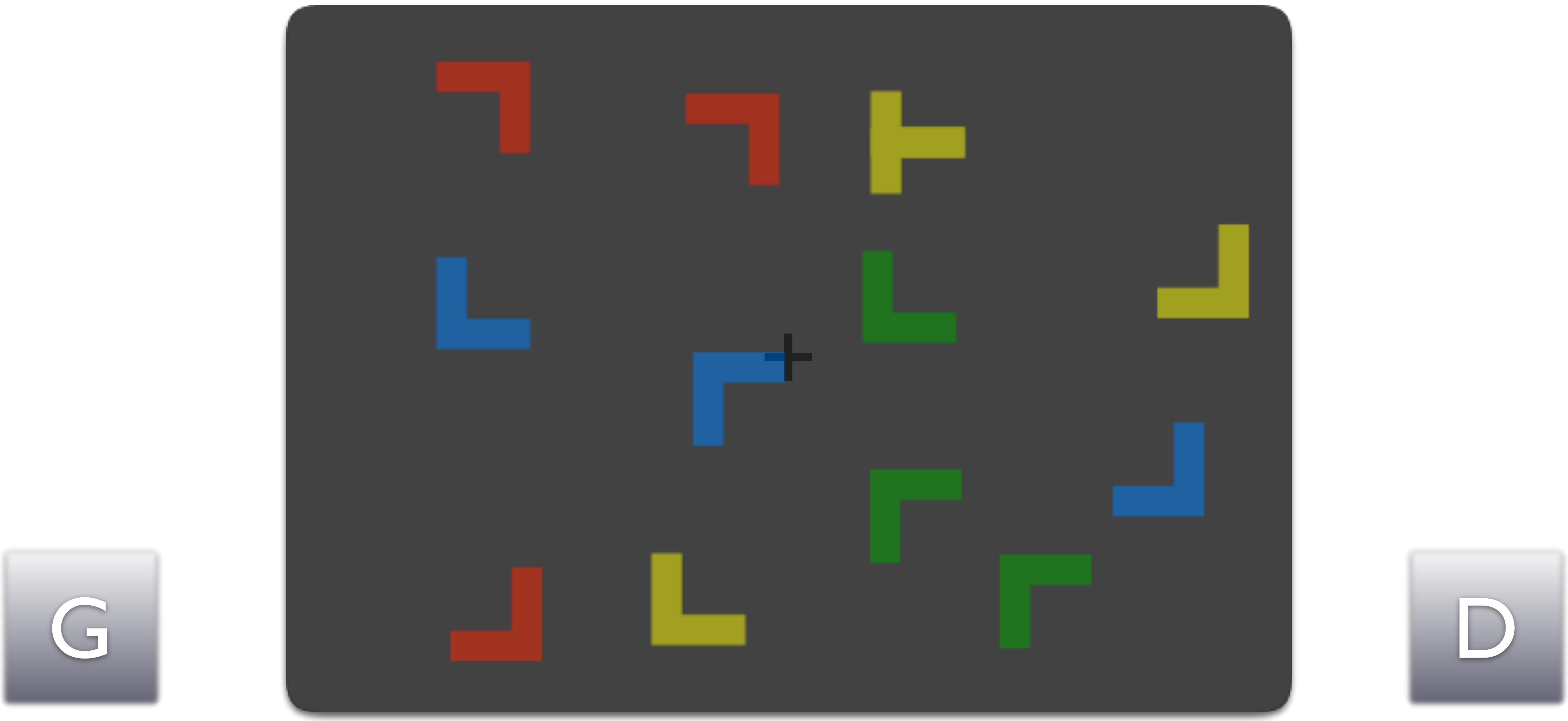
Tâche: Trouver le T et indiquer son orientation

Réponse: “gauche” => appuyer sur la clé pour gauche

Contextes aléatoires



Contextes aléatoires



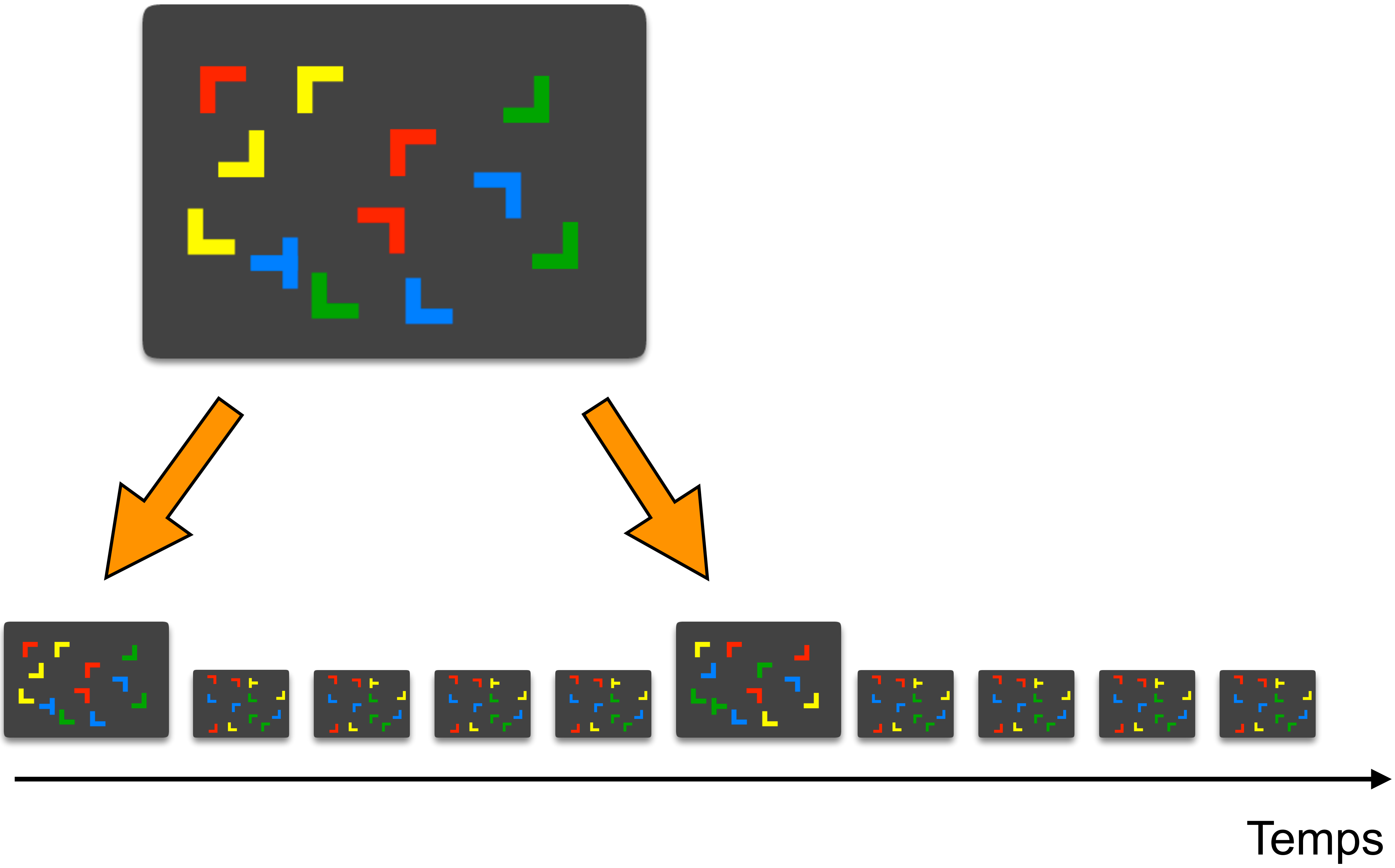
et ainsi de suite...

quelques essais plus tard...

Tâche: Trouver le T et indiquer son orientation

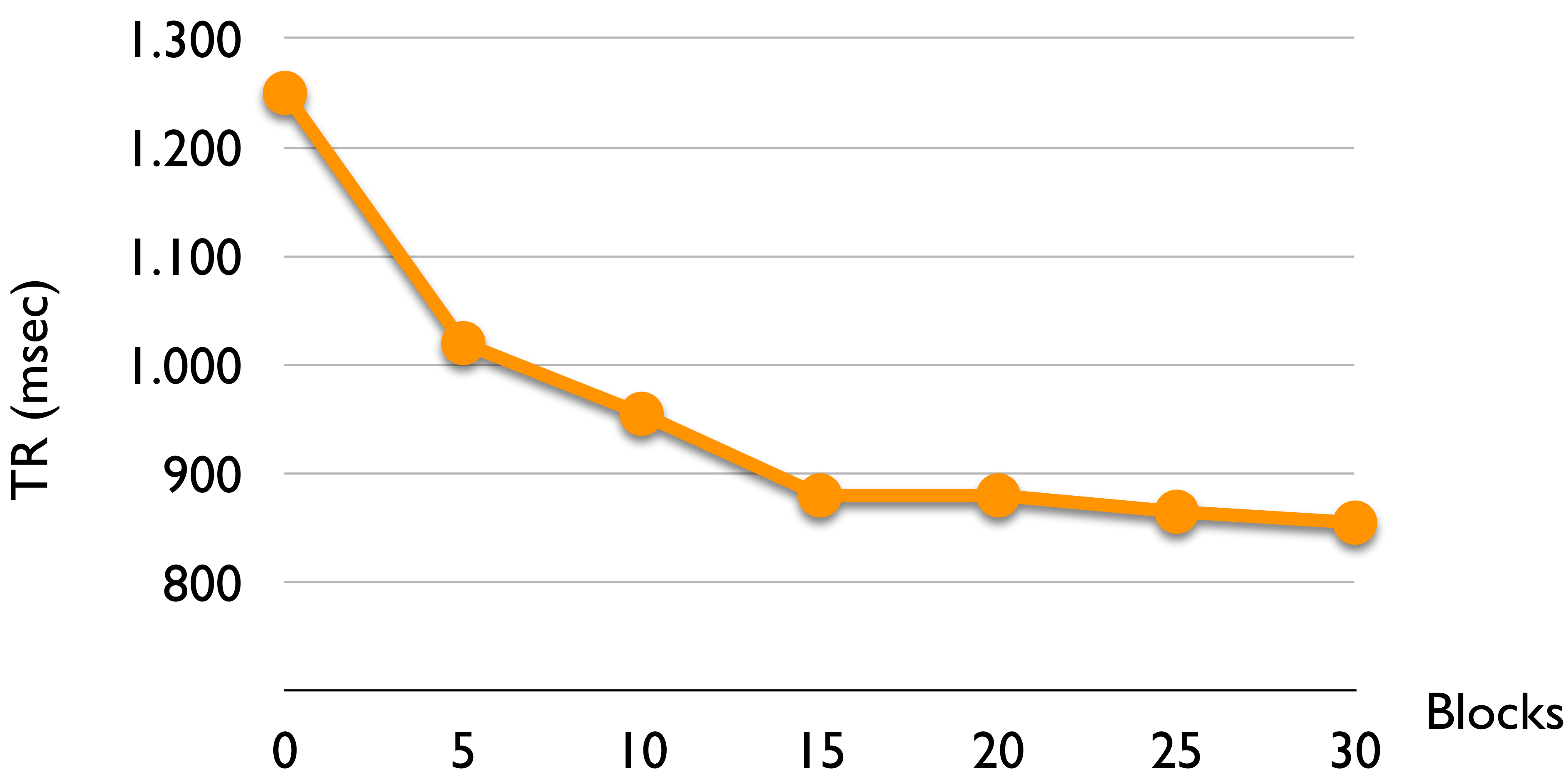
Réponse: “droite” => appuyer sur la clé pour droite

Contextes répétés



Effets d'apprentissage (1)

En générale, les sujets répondent de plus en plus vite

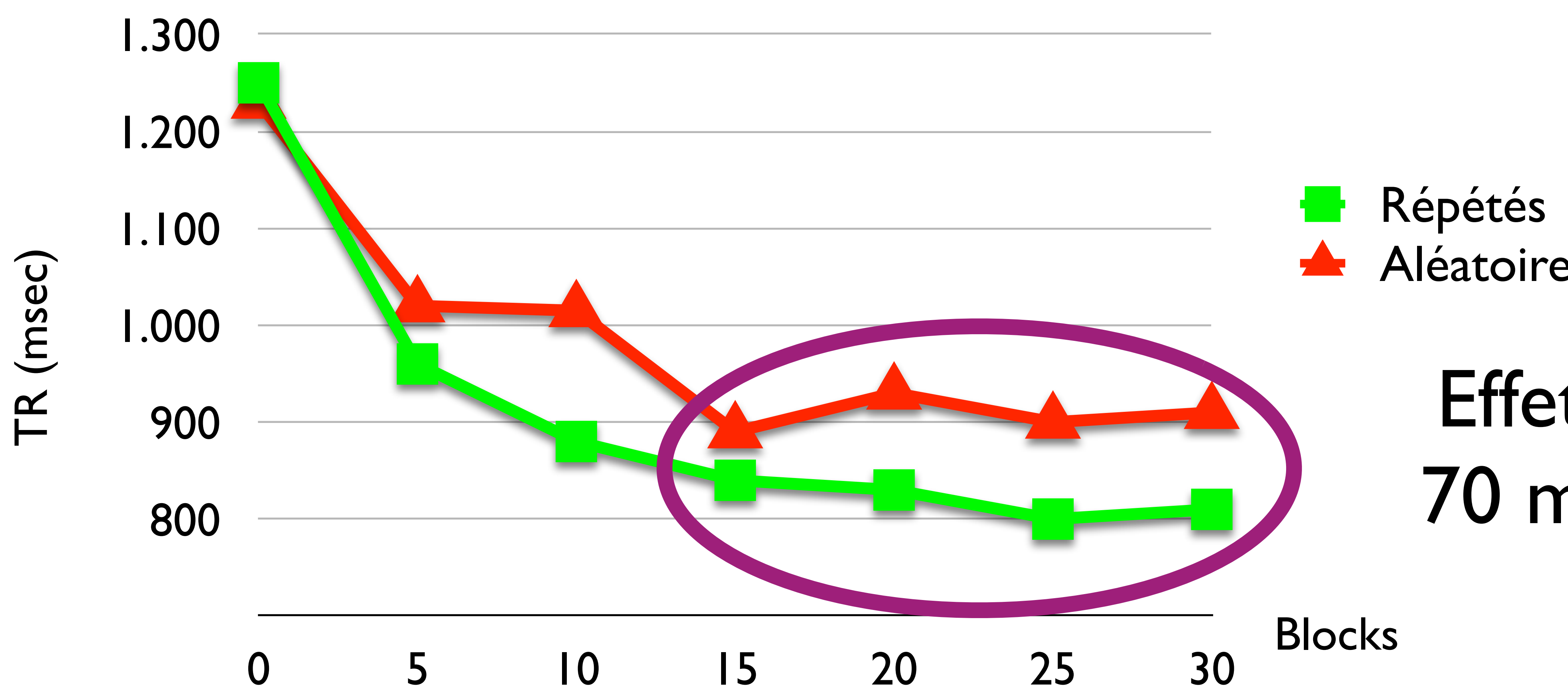


UNIVERSITÉ LIBRE DE BRUXELLES

LA LIBERTÉ DE CHERCHER

Effets d'apprentissage (2)

Mais surtout, les TR pour les contextes prédictifs diminuent encore plus que pour les contextes aléatoires



Effet:
70 ms

Explaining IL

Explaining IL

Initially thought to be unconscious rule abstraction, very much like conscious learning, just without consciousness

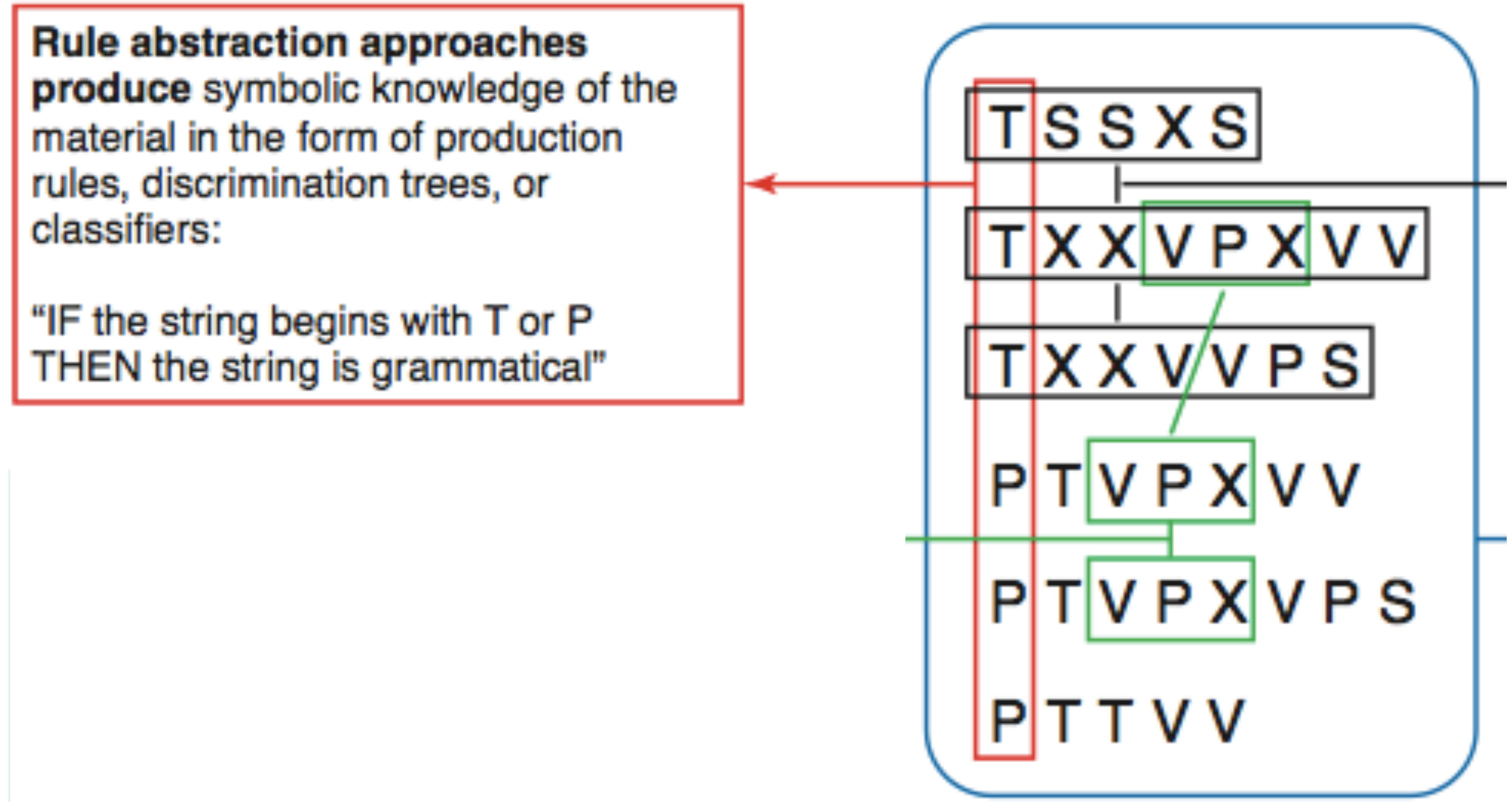


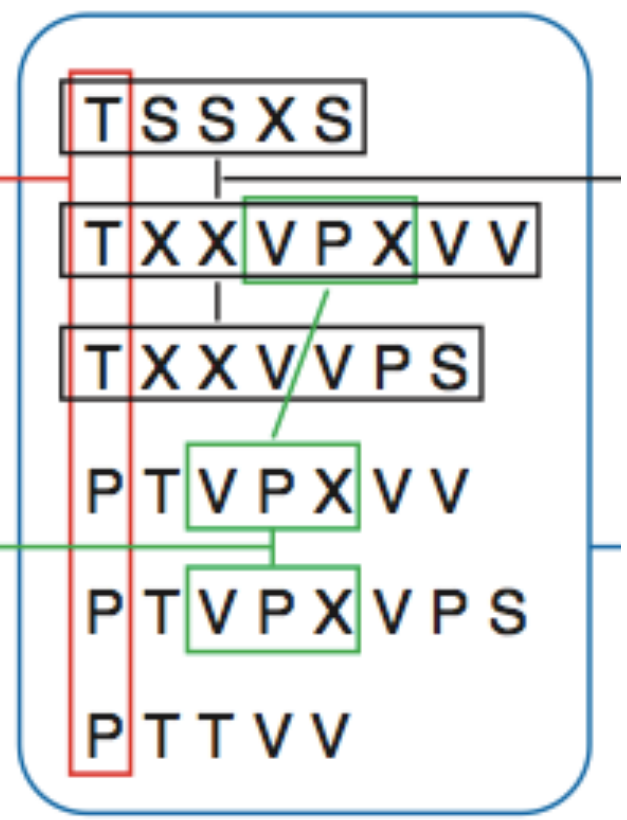
Fig. 1 An illustration of different computational approaches to artificial grammar learning. Each approach makes different assumptions about the processes and knowledge representations involved in memorizing a set of letter strings generated from a finite-state grammar. The same approaches are also relevant to sequence learning paradigms if the strings are taken to be continuous sequences of visual events.

Explaining IL

but there are other possible explanations…

Rule abstraction approaches produce symbolic knowledge of the material in the form of production rules, discrimination trees, or classifiers:

"IF the string begins with T or P THEN the string is grammatical"



Fragment-based and chunking approaches exploit the redundancy of the training material by decomposing it into short chunks such as bigrams or trigrams. The resulting database can be organized hierarchically or not. New exemplars are classified according to how many chunks they share with the training material.

Fig. 1 An illustration of different computational approaches to artificial grammar learning. Each approach makes different assumptions about the processes and knowledge representations involved in memorizing a set of letter strings generated from a finite-state grammar. The same approaches are also relevant to sequence learning paradigms if the strings are taken to be continuous sequences of visual events.

Explaining IL

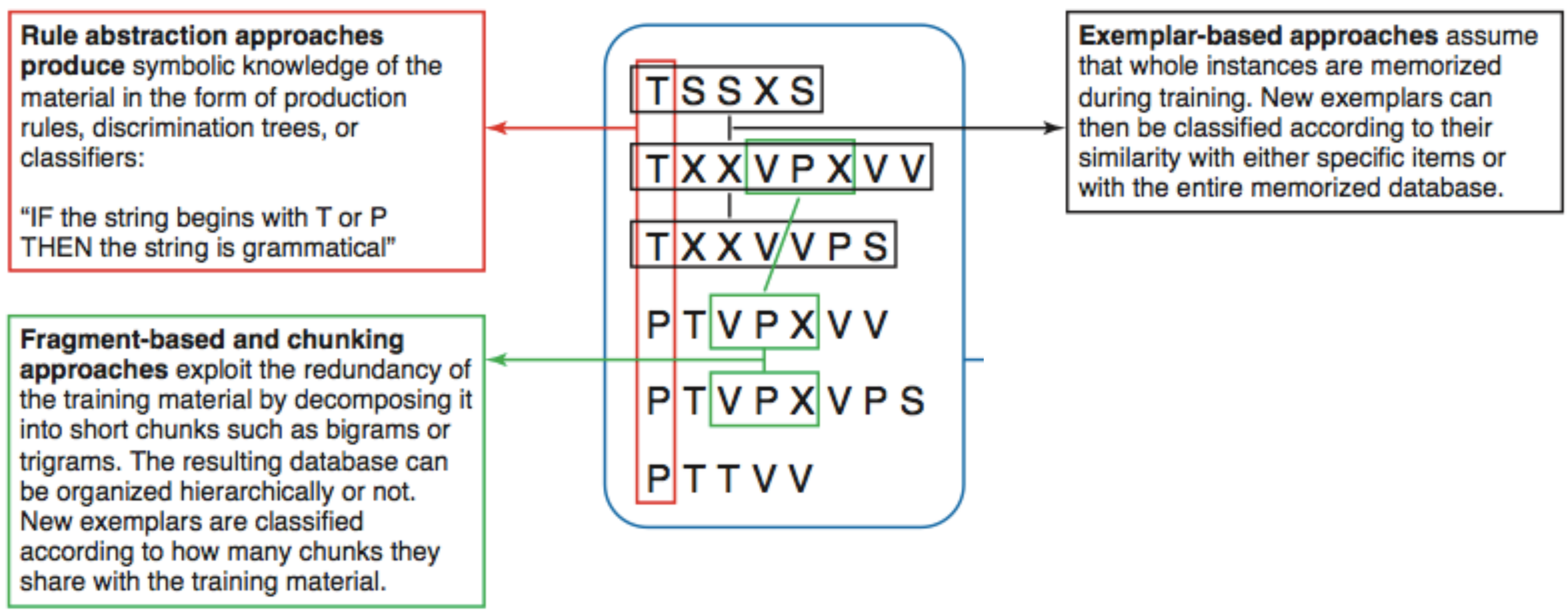


Fig. 1 An illustration of different computational approaches to artificial grammar learning. Each approach makes different assumptions about the processes and knowledge representations involved in memorizing a set of letter strings generated from a finite-state grammar. The same approaches are also relevant to sequence learning paradigms if the strings are taken to be continuous sequences of visual events.

Explaining IL

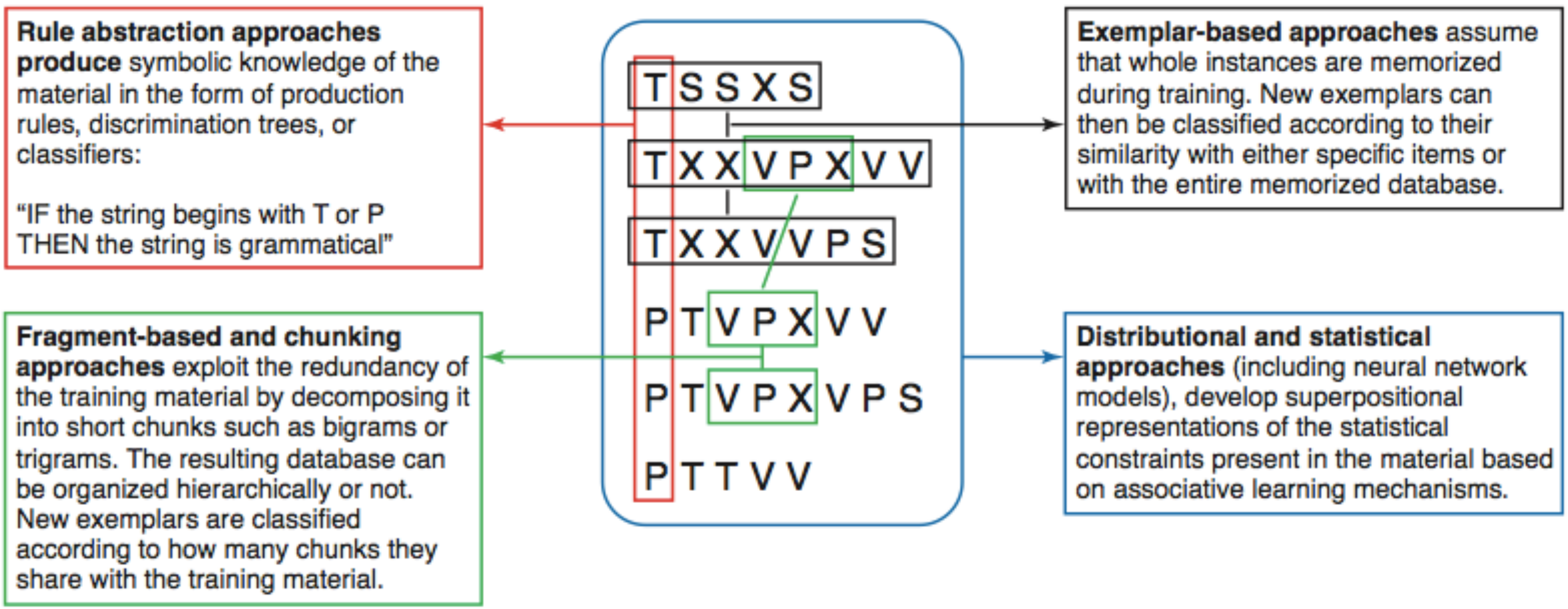


Fig. 1 An illustration of different computational approaches to artificial grammar learning. Each approach makes different assumptions about the processes and knowledge representations involved in memorizing a set of letter strings generated from a finite-state grammar. The same approaches are also relevant to sequence learning paradigms if the strings are taken to be continuous sequences of visual events.

Explaining IL

Today rather seen as an **acquired sensitivity to statistical regularities**.

Cleeremans et al. (1998): "[B]est described as lying somewhere on a continuum between purely exemplar-based representations and more general, abstract representations – a characteristic that **neural-network models** are particularly apt at capturing."

But the debate is far from closed!

Implicit vs. Explicit

Implicit &/vs. Explicit Learning

(Sun et al., 2007)

Characteristics	**Implicit Learning**	**Explicit Learning**
Effort	Easy	Hard
Learning	Unaware	Aware
Robustness	Error tolerant	Error intolerant
Knowledge	Difficult-to-Verbalize	Easy-to-Verbalize
Type of Cognition	Hot (emotional)	Cool
Speed	Fast	Slow
Control	Cue-driven (unconscious)	Conscious
Solutions	Heuristic	Algorithmic
Representation	Holistic	Analytic

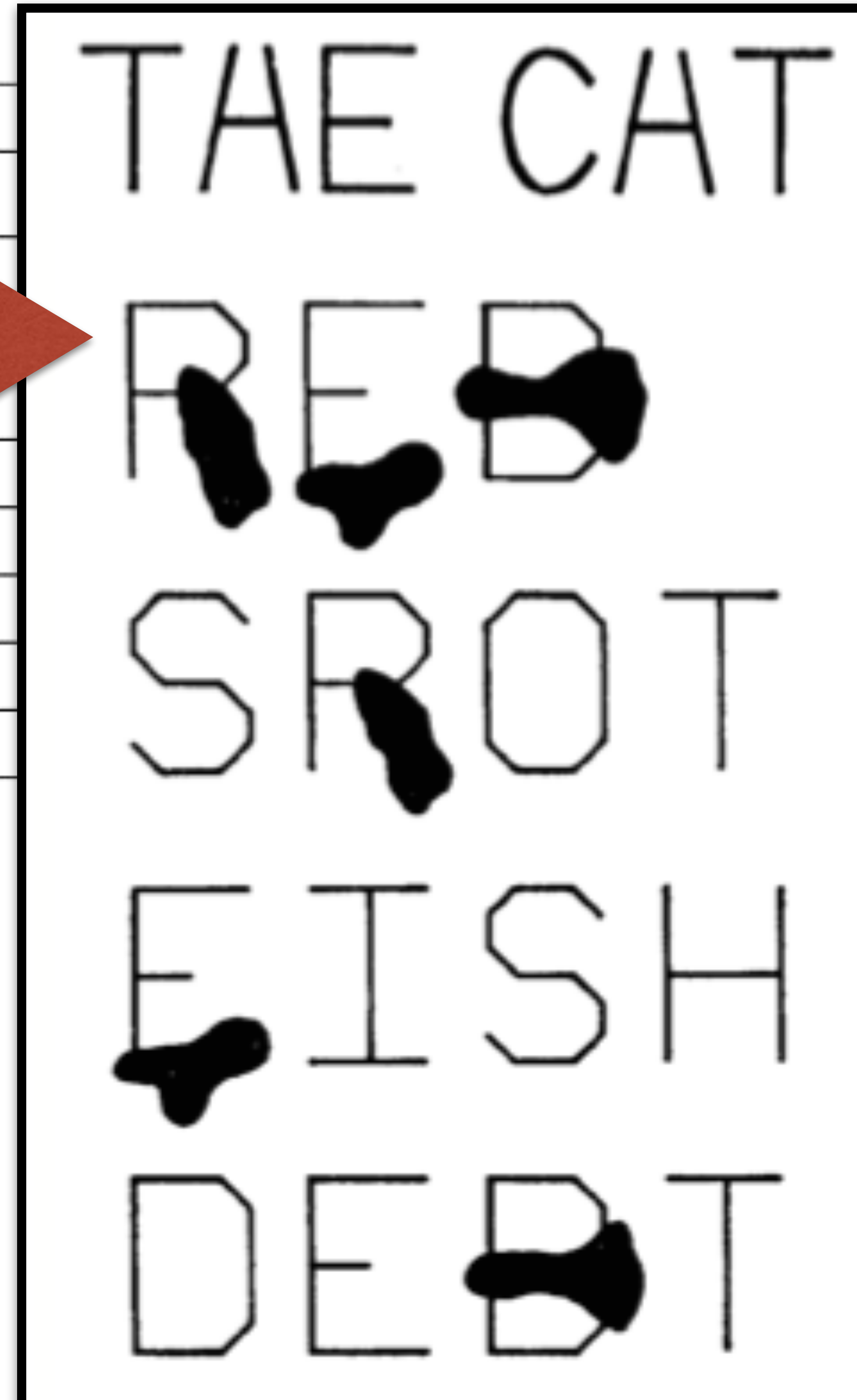
(Reber, 1996)

Age dependence	**Low**	**High**
Interpersonal Variability	**Low**	**High**
IQ dependence	**Low**	**High**

Implicit &/vs. Explicit Learning

(Sun et al., 2007)

Characteristics	**Implicit Learning**
Effort	Easy
Learning	Unaware
Robustness	Error tolerant
Knowledge	Difficult-to-Verbalize
Type of Cognition	Hot (emotional)
Speed	Fast
Control	Cue-driven (unconscious)
Solutions	Heuristic
Representation	Holistic



(Reber, 1996)

Age dependence	**Low**
Interpersonal Variability	**Low**
IQ dependence	**Low**

Implicit &/vs. Explicit Learning

(Sun et al., 2007)

Characteristics	**Implicit Learning**	**Explicit Learning**
Effort	Easy	Hard
Learning	Unaware	Aware
Robustness	Error tolerant	Error intolerant
Knowledge	Difficult-to-Verbalize	Easy-to-Verbalize
Type of Cognition	Hot (emotional)	Cool
Speed	Fast	Slow
Control	Cue-driven (unconscious)	Conscious
Solutions	Heuristic	Algorithmic
Representation	Holistic	Analytic

(Reber, 1996)

Age dependence	**Low**	**High**
Interpersonal Variability	**Low**	**High**
IQ dependence	**Low**	**High**

Implicit &/vs. Explicit Learning

- IL research has strongly focused on trying to dissociate the two forms of learning
- Interactions between the two forms of learning are rarely considered nor studied
- But, very likely to co-contribute to our everyday learning processes
- There are no process-pure measures of learning, the black-or-white dichotomy is unrealistic

Relevance for Schools?

Relevance for Schools?

- "Learning" is not just restrained to what happens in schools
- IL research show that **we are natural-born learners!**
- IL likely a phylogenetically older form of learning
- IL seems to be the default mode of learning, "what the brain does all the time"(=> neuroplasticity)
- IL is very likely to happen "all the time", thus also in school contexts, but may go unnoticed by teachers and learners

Relevance for Schools?

- Since IL is relatively specific and does not flexibly transfer to new stimuli, helping students to become aware of important rules is still necessary
- Learners may learn certain things implicitly that we do not want them to learn
- My claim: We can only gain from better understanding the effects of IL processes on school-based learning processes

Better understand learning processes

Better understanding

- IL has rather weak effects, at least at the beginning
- IL is difficult to control "from the outside"
- IL takes time! Do not expect "miracles"!
- Mastery requires cognitive efforts!

Better understanding

- IL does not produce the same type of knowledge that EL does
- IL and EL can lead to "conflicting" knowledge
- IL is particularly active when the content domain contains task-relevant "hidden" complex structural information
- EL is particularly useful when it comes to memorizing "simple" rules

Better understanding

- If you want to detect IL you need to design adapted assessments
- Rule-like behavior does not necessarily mean rule-based cognition
- Better understand certain errors

Design better learning situations

Better design

- Sun et al. (2007): "Most educational settings focus on teaching **conceptual** (explicit) knowledge rather than setting up an opportunity for gaining substantial **experiential** (mostly implicit) knowledge. While this may be appropriate for some subject areas, other subjects areas **may require learning information** (e.g., features of complex systems or categories) **that are better learned** (at least initially) **through extensive hands-on experience than with lectures or textbooks alone** (that is, with explicit learning alone)."

Better design

- IL-based teaching scenarios will never replace or eliminate the need for EL-based ones, but they can complement them
- If we allow for IL processes to build up sensitivities to statistical regularities contained in a knowledge domain, we allow learners to become "naturally fluent" before helping them to establish conceptual, symbolic and explicit knowledge

Better design

- IL may be advantageous for learners less "keen" on top-down conceptual instruction
- Enable "flow" by proposing easy and incidental learning situations

Better design

- We can allow for variations around a prototype, kids' brains can handle this! (Example: written letters)
- We need to carefully think about the learning materials we use and the statistical regularities they contain
- Many video games seem to implement such incidental learning situations, cf. "discovery learning"

Future directions

Future directions

- Invitation to design IL-informed learning scenarios that can be tested in controlled laboratory settings first and than "in the wild"
- Design-Based Research Approach (Brown, 1992) seems promising for NeuroEducation

Thank you for your **attention**