The connection between statistical learning and reading: how far does it go?

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The reading paradox

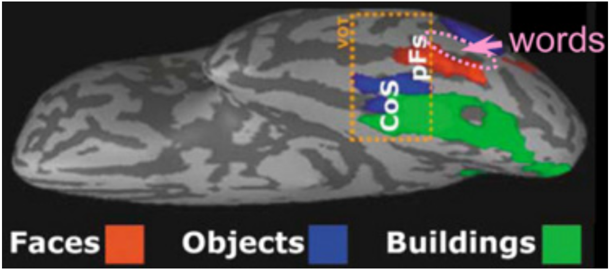
We're fantastic readers...

- We can identify words in ~35ms and without awareness (e.g., Forster and Davis, 1984)
- We read ~260 words per minute (e.g., Brysbaert, 2019)

...and yet, no direct genetic endowment

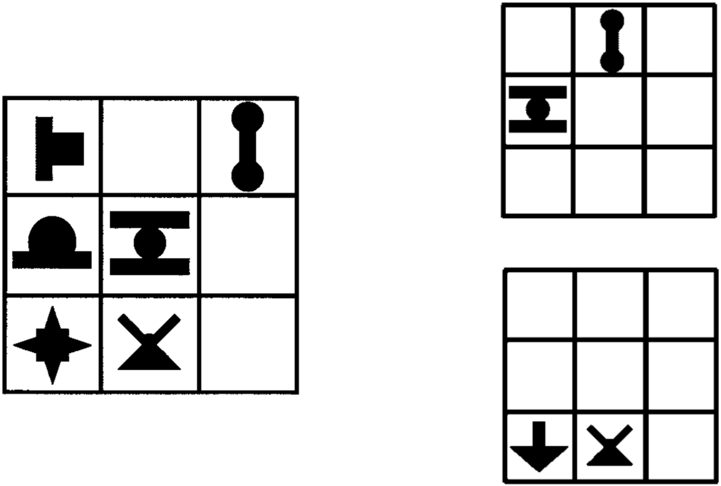
- Written language is a recent invention (~5.5K ya)
- Written language isn't observed universally
- Literacy isn't acquired spontaneously

The reading paradox



(Dehaene and Cohen, 2007)

Statistical learning in visual scenes



(Fiser and Aslin, 2001)

Statistical learning in the lexicon

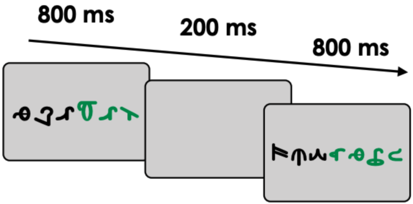
- Words as ordered chunks of letters
- Morphemes as recurring chunks of letter

- There's *corn* in *corner* and *iron* in *irony* (e.g., Longtin et al., 2003; Rastle et al., 2004)
- *gasful* is trouble, but *fulgas* is not (e.g., Crepaldi et al., 2010)

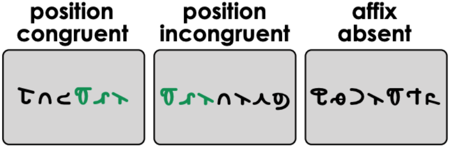
The statistical learning of affixes

Artificial affixes

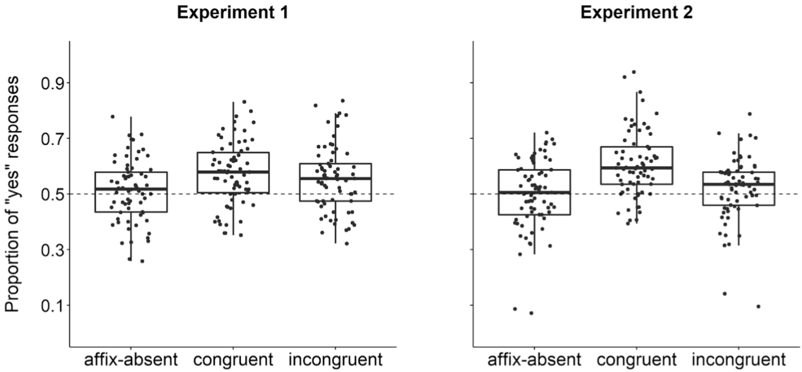
Training



Testing



Results



(Lelonkiewicz et al., 2020)

Visual affixes

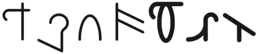
Our chunks:

- clusters of pseudo-letters that occur together frequently across different items
- no contact with phonology, semantics or syntax

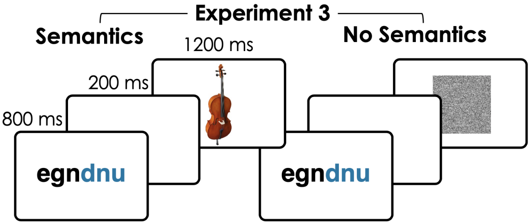
And yet:

- sensitivity to these chunks
- sensitivity to their position (e.g., Crepaldi et al., 2010)

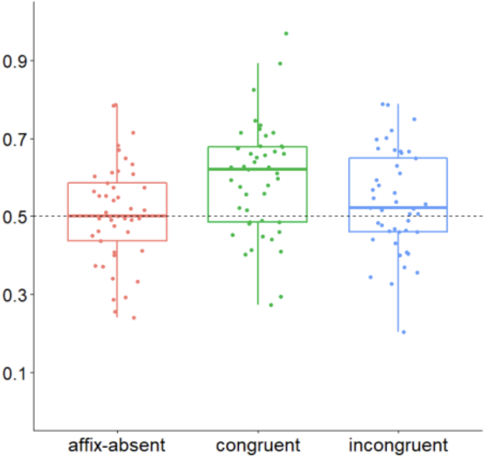
Stairway to language



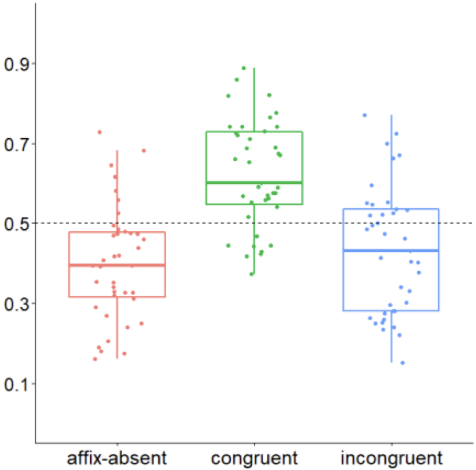
abtqkrv



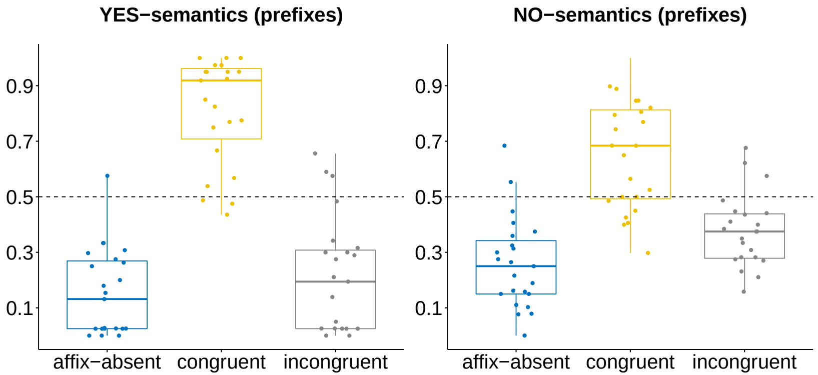
One step down: abstract shapes



One step up: real letters



Two steps up: meaning



Take home message

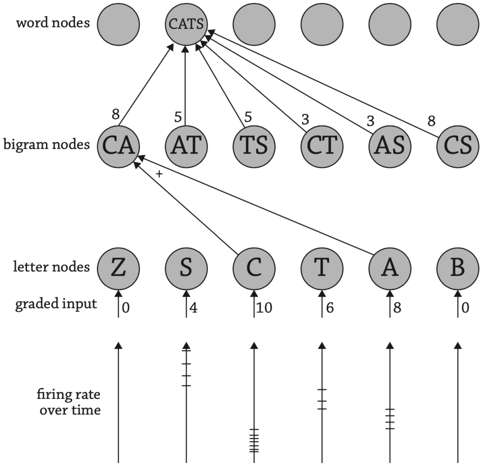
- Readers spontaneously extract visual statistical regularities and use them to identify affix-like character chunks
- Such learning occurs in purely visual and language-like material, showing that the core computational engine is not language-specific
- Such learning is, however, enhanced by the availability of linguistic information (phonology and meaning)

More about this?

- Lelonkiewicz, J., Ktori, M. and Crepaldi, D. (2020). Morphemes as letter chunks: Discovering affixes through visual regularities. *Journal of Memory and Language*, 115, 104152
- Lelonkiewicz, J., Ktori, M. and Crepaldi, D. (2021). Morphemes as letter chunks: Linguistic information enhances the learning of visual regularities. In revision at *Journal of Memory and Language*

Does this go beyond morphology?

Bigrams


word nodes
CATS
8
5
5
3
3
8
bigram nodes
CA
AT
TS
CT
AS
CS
+
letter nodes
Z
S
C
T
A
B
graded input
0
4
10
6
8
0
firing rate
over time

Phantom words (Endress and Mehler, 2009)

ABF

DBC

AEC

Phantom words (Endress and Mehler, 2009)

ABF

DBC

AEC

ABC

Phantom words (Endress and Mehler, 2009)

ABF

DBC

AEC

DEF

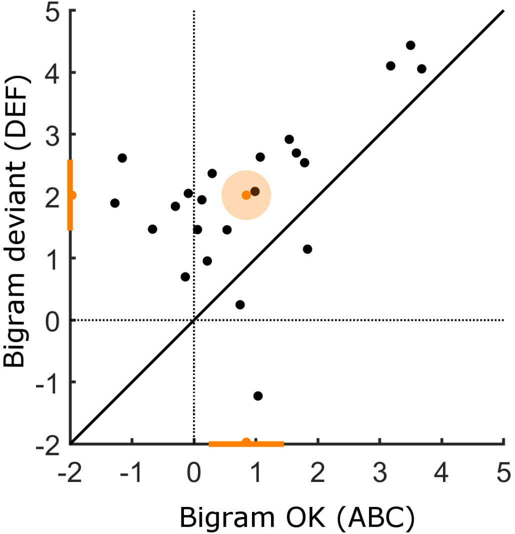
Phantom words (Endress and Mehler, 2009)

ABF
DBC
AEC

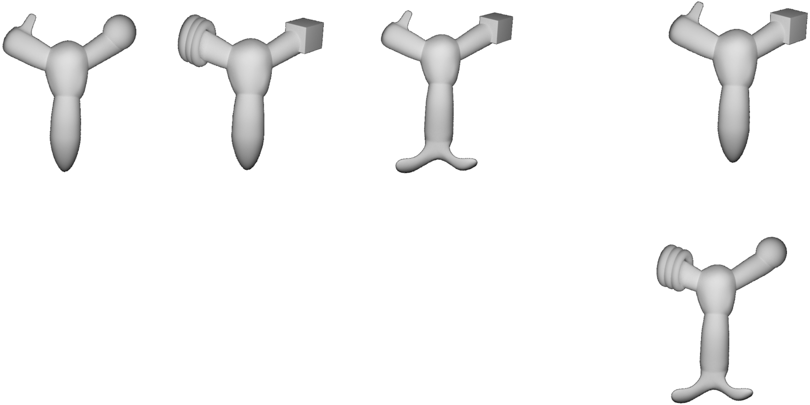
ABC
DEF

Pseudo–letters (Vidal et al., 2017)

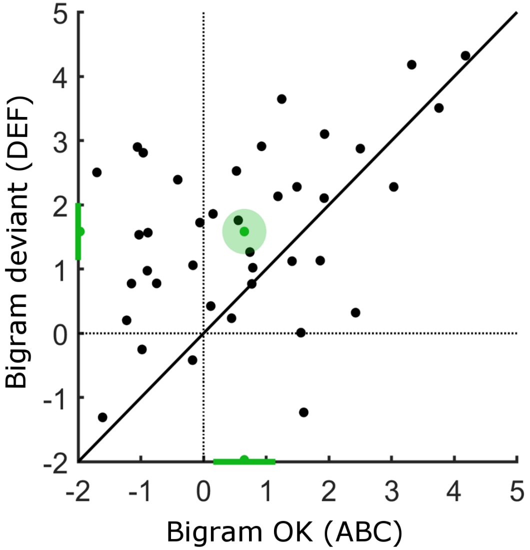
Results



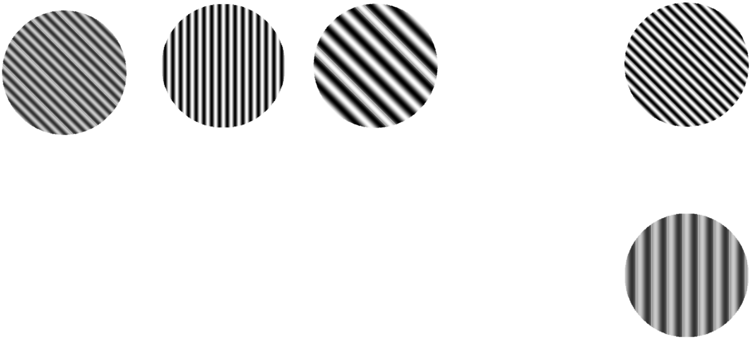
Phantom tripods



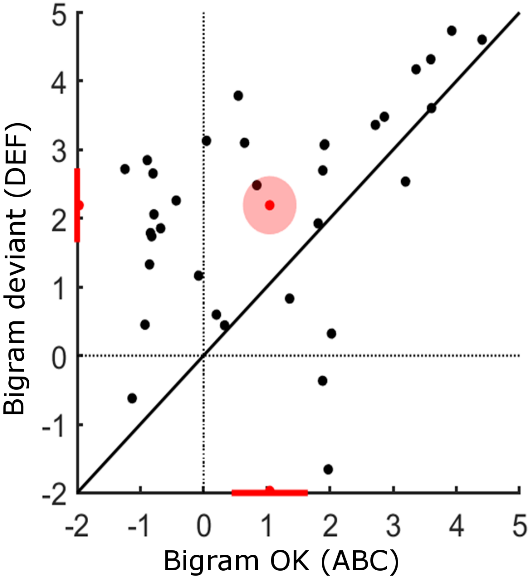
Phantom tripods



Phantom Gabors



Phantom Gabors



Take–home message

- We code for nGrams/letter transition stats while learning novel words
- We use the same mechanism while learning novel objects, where the lower–level units are:
  - not arranged horizontally, and very different visually from letters
  - not even spatially segregated

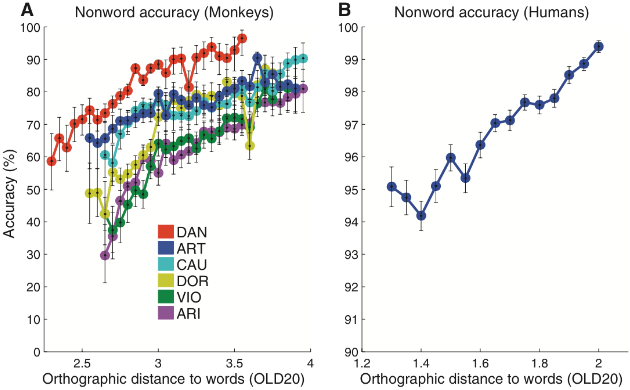
- Word learning shares (part of) its computational core with vision

More about this?

- Vidal, Y., Viviani, E., Zoccolan, D. and Crepaldi, D. (2021). A general-purpose mechanism of visual feature association in visual word identification and beyond. *Current Biology*, 31, 1261-1267.

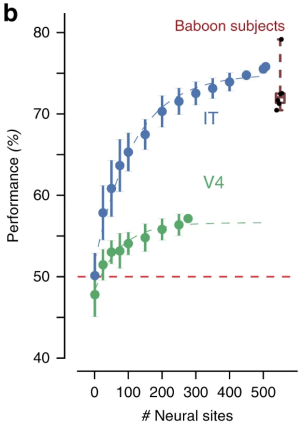
Do we see orthographic in non-linguistic animals?

Orthographic coding in Baboons



(Grainger et al., 2012)

The neural counterpart



(Rajalingham et al., 2020)

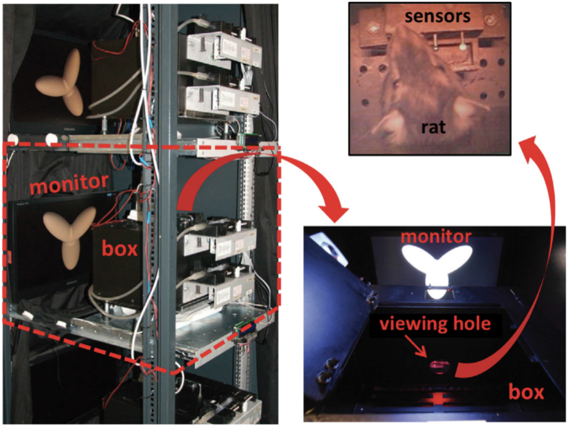
Proof-of-principle

- Grainger et al. (2012): behaving animals, whole-sale approach
- Rajalingham et al. (2020): more details, but artificial models

Long-Evans rats

- A jump back in evolution
- Low acuity
- Object invariance is not entirely clear (e.g., Tafazoli et al., 2017; Vinken and Op De Beeck, 2021)

The setup

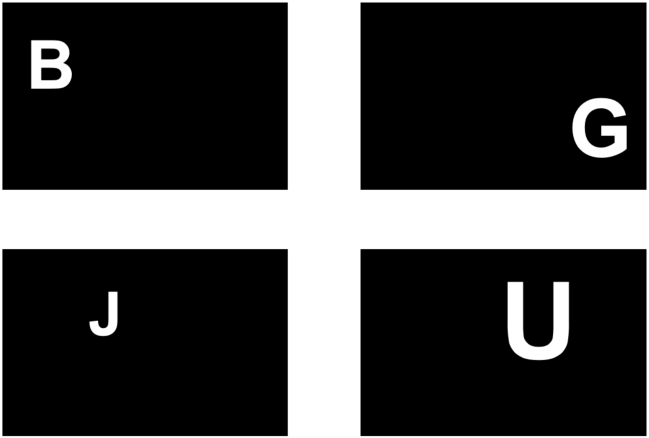


Letter identification

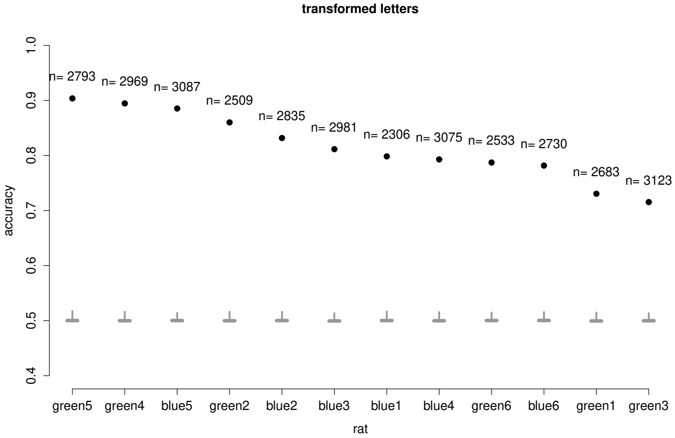
Go-left letters

Go-right letters

Letters as abstract objects



Letters as abstract objects



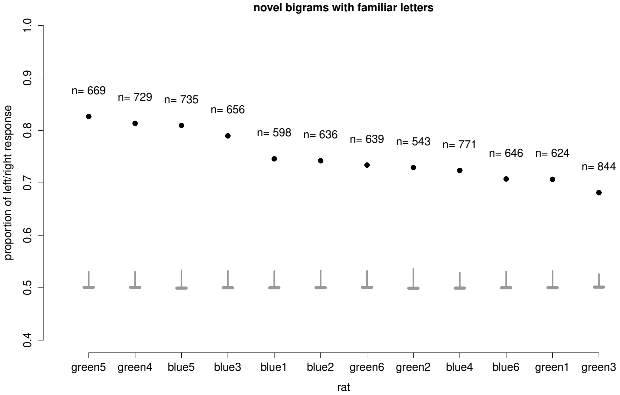
A rodent model of visual word identification

- Learn to identify letters with at least some degree of invariance

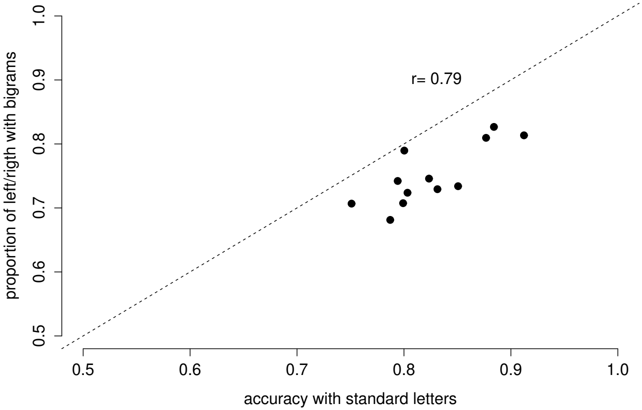
Letters in bigrams

B M

Letters in bigrams



Letters in bigrams



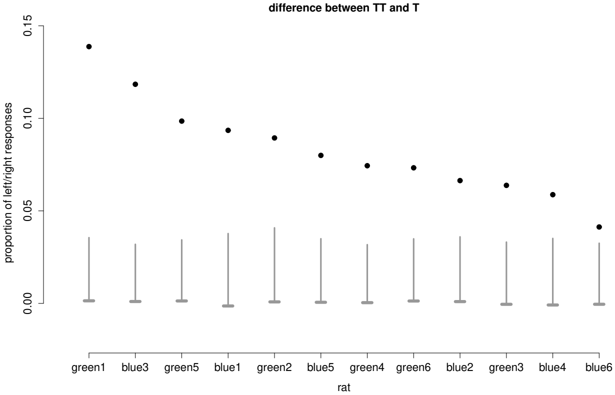
A rodent model of visual word identification

- Learn to identify letters with at least some degree of invariance
- Identify individual letters as independent objects within bigrams

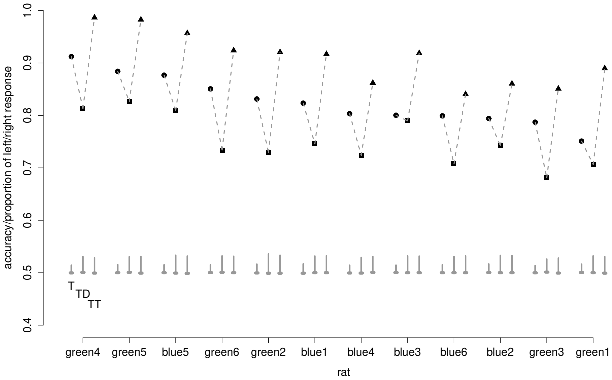
Two familiar letters

B U

Letter integration into bigrams



Letter integration into bigrams

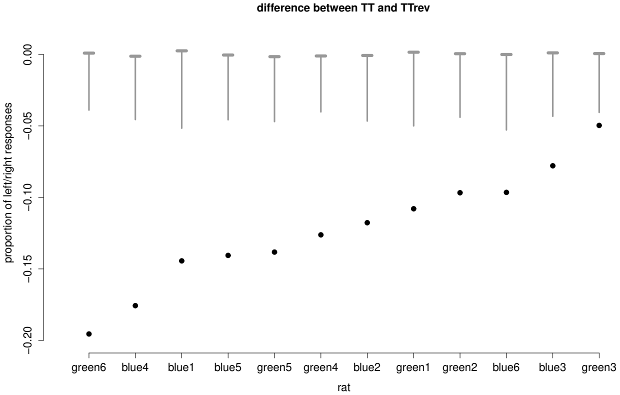


A rodent model of visual word identification

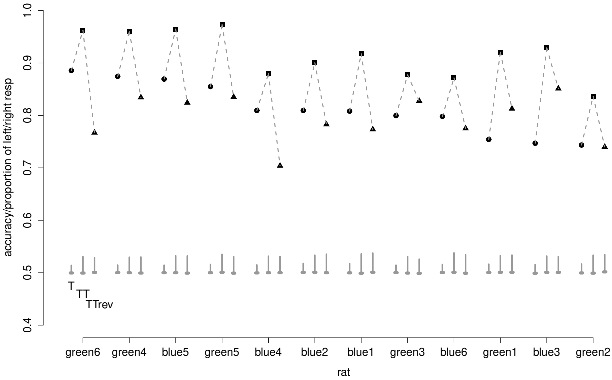
- Learn to identify letters with at least some degree of invariance
- Identify individual letters as independent objects within bigrams
- Use information from multiple letters within bigrams

Transposed letter effects

Letters are identified, still



But position is coded, too



A rodent model of visual word identification

- Learn to identify letters with at least some degree of invariance
- Identify individual letters as independent objects within bigrams
- Use information from multiple letters within bigrams
- Identify letters in a position-invariant way
- Code for letter position within bigrams

- Rats **spontaneously** process bigrams orthographically, given familiarity with letters

Acknowledgments

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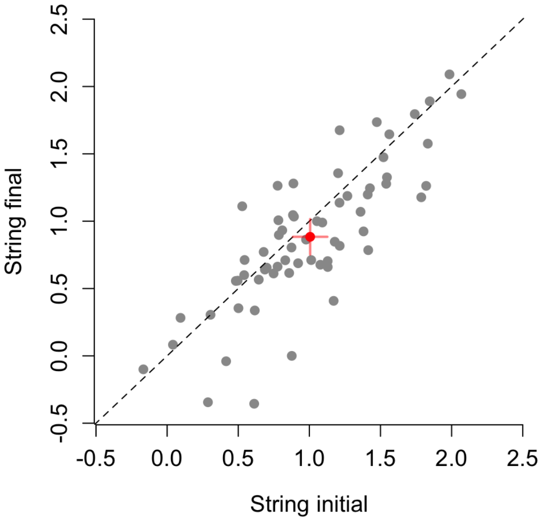
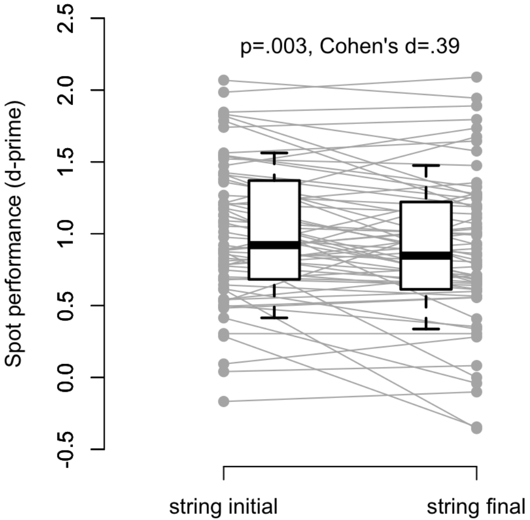
String initial chunks are easier to detect



String initial chunks are easier to detect



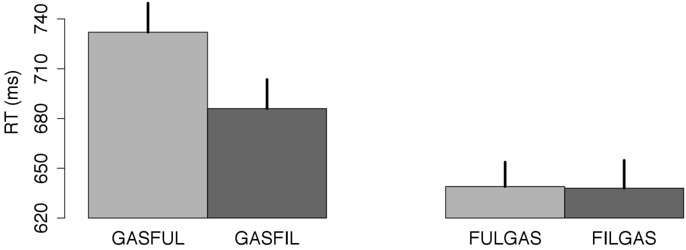
Orthographic coding

> *"I will assume that most of the information used by skilled readers to silently read words for meaning concerns information about abstract (i.e., case and font independent) letter identities, plus information about letter positions – in other words, orthographic information"*

(Grainger, 2018)

Blind to suffixes?

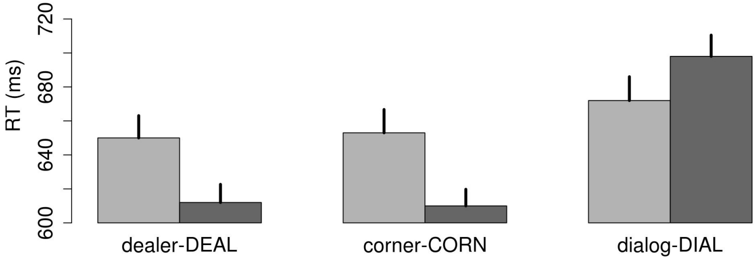
- (GASFUL vs. GASFIL) vs. (FULGAS vs. FILGAS)



(Crepaldi et al., 2010)

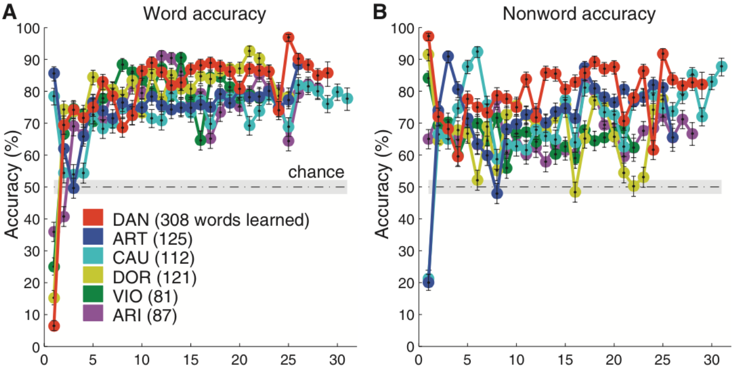
Corners that corn

dealer–DEAL vs. corner–CORN vs. dialog–DIAL



(Rastle et al., 2004)

Orthographic coding in Baboons



(Grainger et al., 2012)

A new approach to reading

- Scripts can be seen as fully–fledged visual systems
- They can be studied as such, without language
- The way we learn to deal with them can be captured through statistical learning
- The way we learn to map them onto language can be captured through statistical learning

The Statistical Learning principle

- Find regularities in low–level objects. . .
- . . . and build higher–level units based on this regularities