#### Dr Maria Korochkina

# Learning affixes through text experience: A new theoretical and computational framework

CBU @ Cambridge 9 October 2025





# What is morpheme knowledge for?

Most English words are built by recombining stems and affixes

<u>clean</u>er, <u>clean</u>ly, un<u>clean</u> teach<u>er</u>, bank<u>er</u>, build<u>er</u>

- Morpheme knowledge enables rapid access to the meanings of familiar words
- It is also crucial for computing the meanings of unfamiliar words

### How is morpheme knowledge acquired?

- Limited time for explicit instruction in school
- Teacher knowledge often patchy





- Form-meaning relationship more salient in written language
  - bon<u>us</u>, atl<u>as</u>, serv<u>ice</u>, princ<u>ess</u> vs. hazard<u>ous</u>
    - → Morpheme knowledge largely acquired via text experience

# Pre-requisites for morpheme learning

<u>un</u>known <u>de</u>activate unfair decode

<u>un</u>afraid <u>de</u>compose

<u>un</u>likely <u>de</u>mand <u>un</u>convinced <u>de</u>ceive <u>un</u>sure <u>de</u>pend

<u>un</u>well <u>de</u>liver (de- + -liberare)

- Must have consistent meaning transformation
- Must occur with a high number of distinct stems (type frequency)
- Must be detectable

# What's children's experience of morphology like in the wild?

A corpus linguistics approach

#### The Children & Young People's Books Lexicon

7-9 years



10-12 years



13+ years

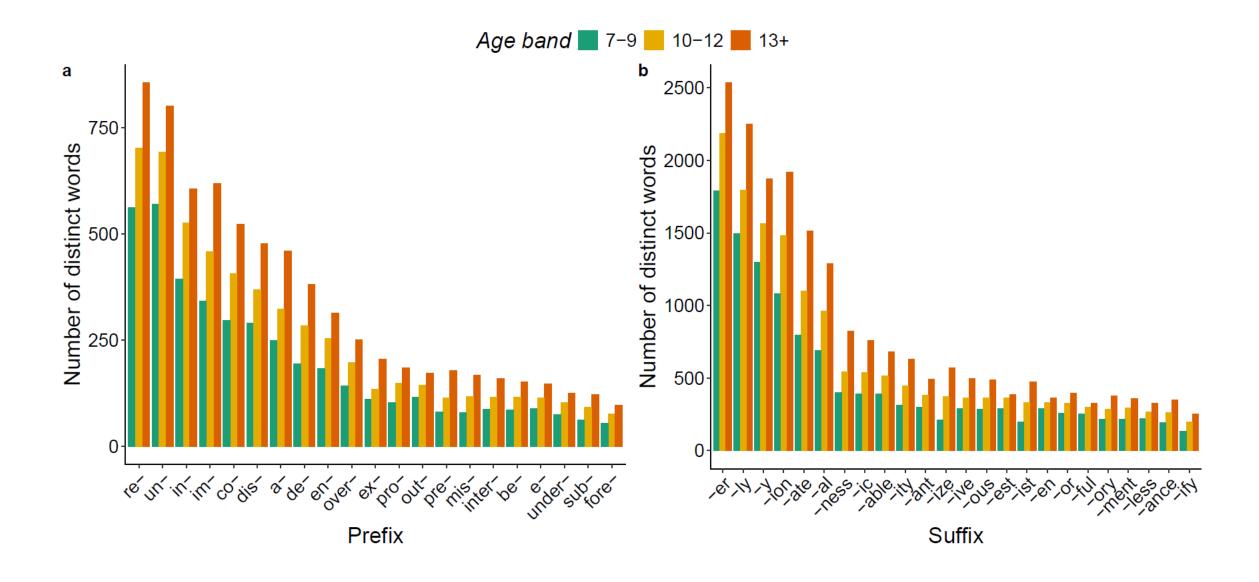


- 1,200 popular books, 400 books per age band
- Over 70 mln words & over 105,000 distinct words

### Morphology in children's books

- Roughly half of all distinct words are complex
- Few complex words are used repeatedly or in many books
- Children are likely to see a complex word but unlikely to see this word again

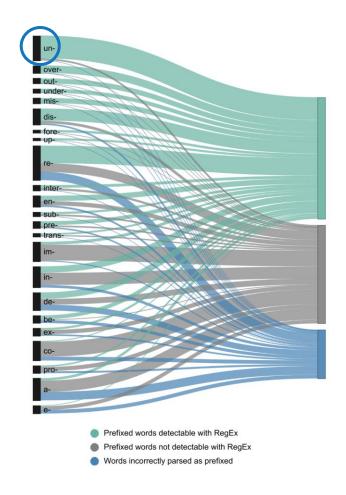
Only a few affixes have reasonably high type frequency before 13+ texts

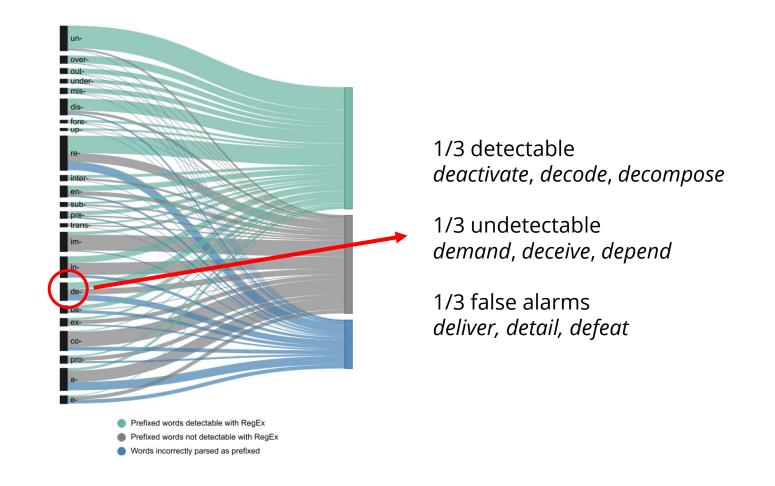


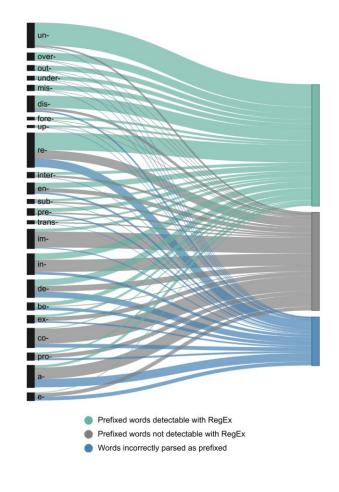
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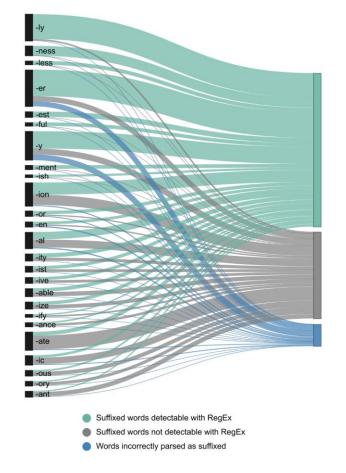
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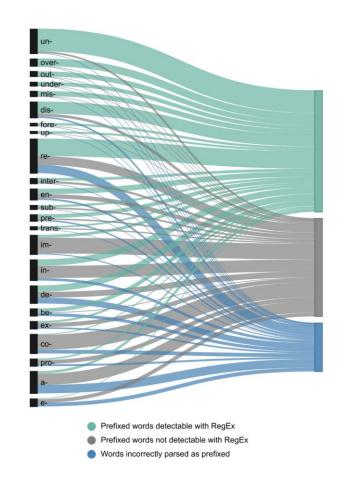
- Only a few affixes have reasonably high type frequency before 13+ texts
- Many affixes difficult to detect

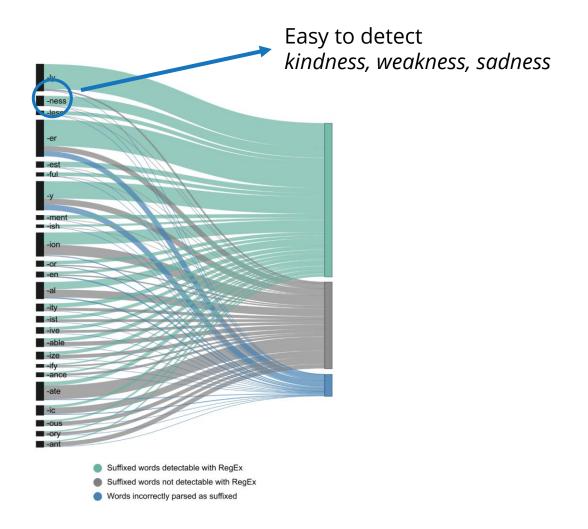


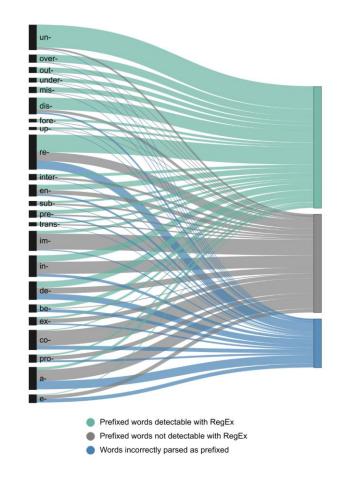


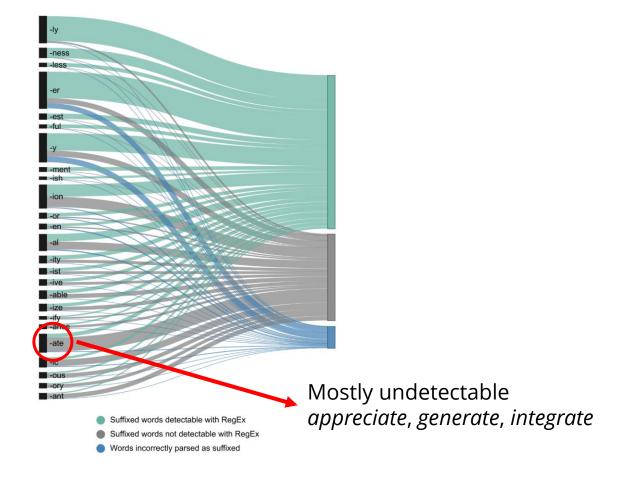


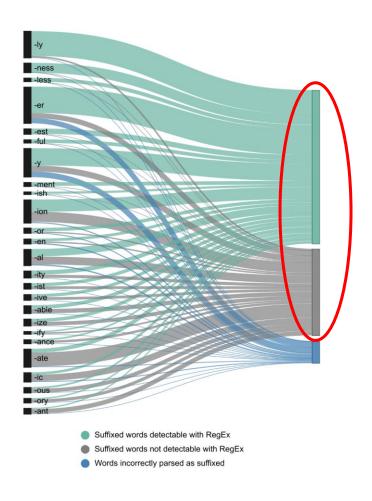




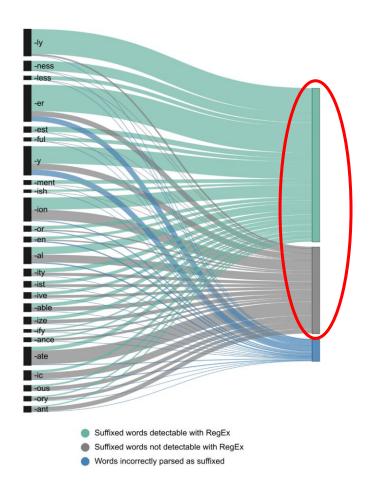




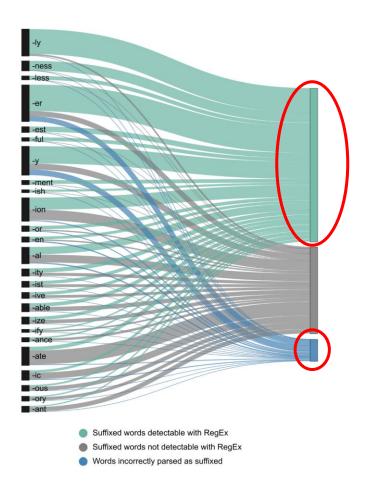




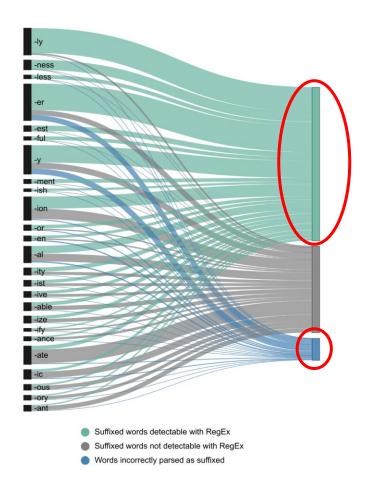
1. All instances where a complex-looking word is **historically formed through derivation** 



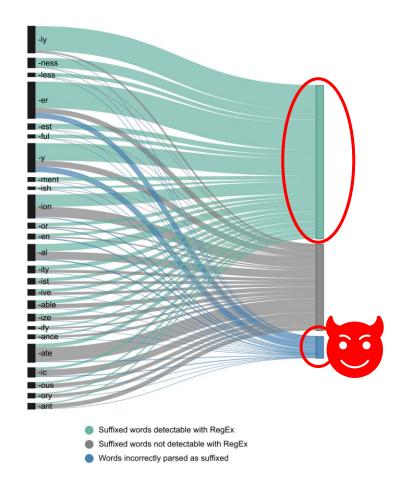
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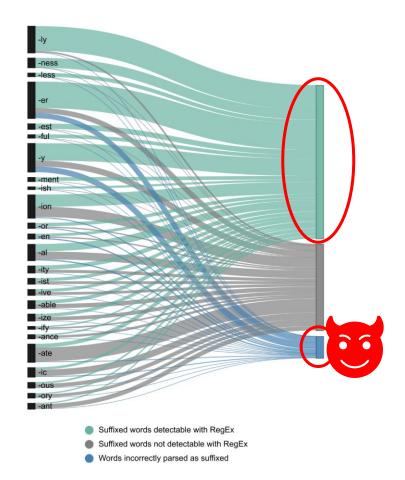
- All instances where a complex-looking word is historically formed through derivation dictionary-based type frequency
- All instances where affixes are identifiable without specialised knowledge



- All instances where a complex-looking word is historically formed through derivation dictionary-based type frequency
- 2. All instances where affixes are **identifiable** without specialised knowledge orthography-based type frequency

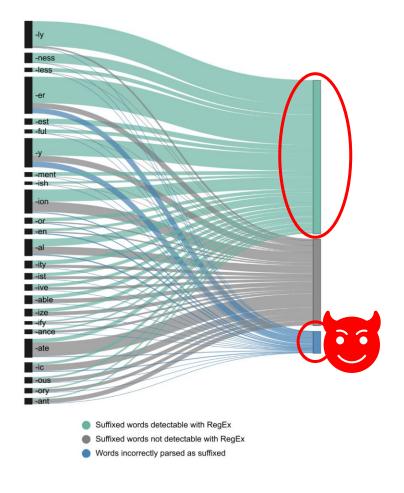


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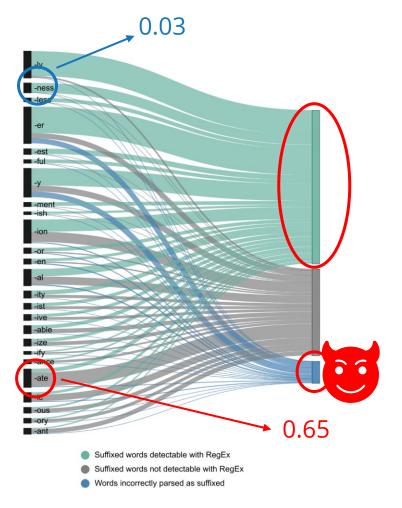
# The false alarm penalty



#### **Shannon entropy**

Quantifies the **uncertainty about the function** of the orthographic pattern associated with an affix

### The false alarm penalty



#### **Shannon entropy**

Quantifies the **uncertainty about the function** of the orthographic pattern associated with an affix

Low entropy → little uncertainty → low penalty

High entropy → more uncertainty → high penalty

#### Theories in action

Which definition best explains human behaviour?

#### The morpheme interference effect

woodness word not a word woodnels
word not a word

- Morphologically-structured nonwords are more difficult, and take longer, to reject
- Skilled readers segment complex-looking words into morphemes

#### Stimuli

- 6 prefixes
  - un-, mis-, dis-, pre-, de-, re-
- 6 suffixes
  - -ness, -ly, -able, -er, -ic, -ate

- Morphologically structured nonwords
  - <u>un</u>wood, wood<u>ness</u>
- Nonwords without morphological structure
  - <u>ub</u>wood, wood<u>nels</u>

- Each participant saw...
  - Each affix with 10 stems (120 morphologically structured nonwords)
  - Orthographic controls (120 nonwords with no morphological structure)
  - 120 morphologically complex + 120 morphologically simple words

#### Stimuli

- 6 prefixes
  - un-, mis-, dis-, pre-, de-, re-
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- Morphologically structured nonwords
  - <u>un</u>wood, wood<u>ness</u>
- Nonwords without morphological structure
  - <u>ub</u>wood, wood<u>nels</u>

- Each participant saw 480 letter strings
  - Each affix with 10 stems (120 morphologically structured nonwords)
  - Orthographic controls (120 nonwords with no morphological structure)
  - 120 morphologically complex + 120 morphologically simple words

#### **Participants**



120 participants



18 – 40 years old

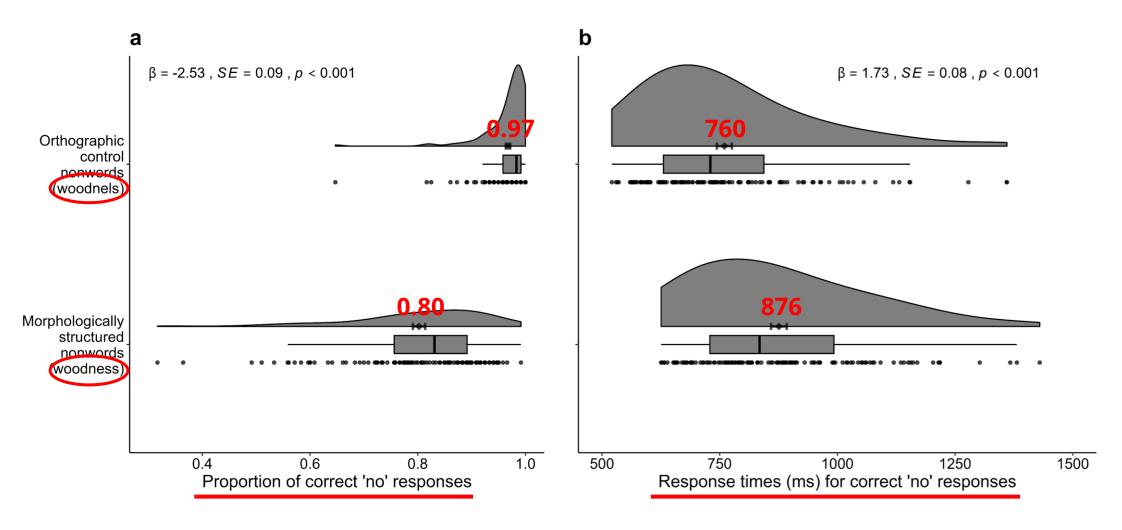


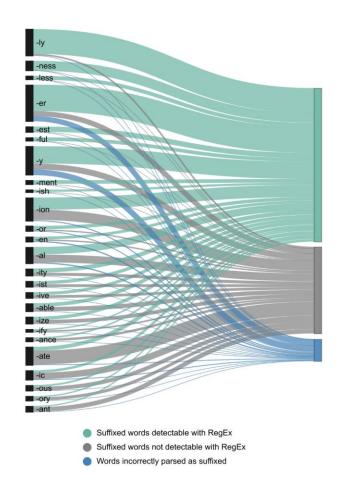
63 female 56 male 1 non-binary



UK based English as a first language No language disorders

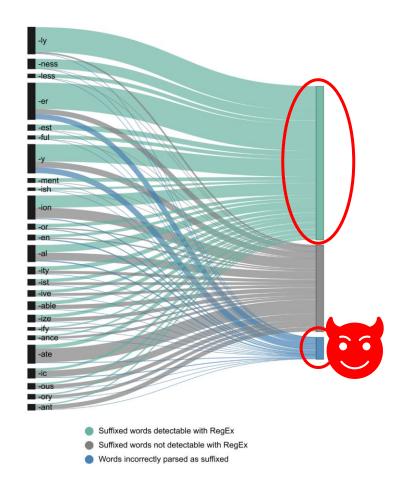
### Readers are sensitive to morphological structure





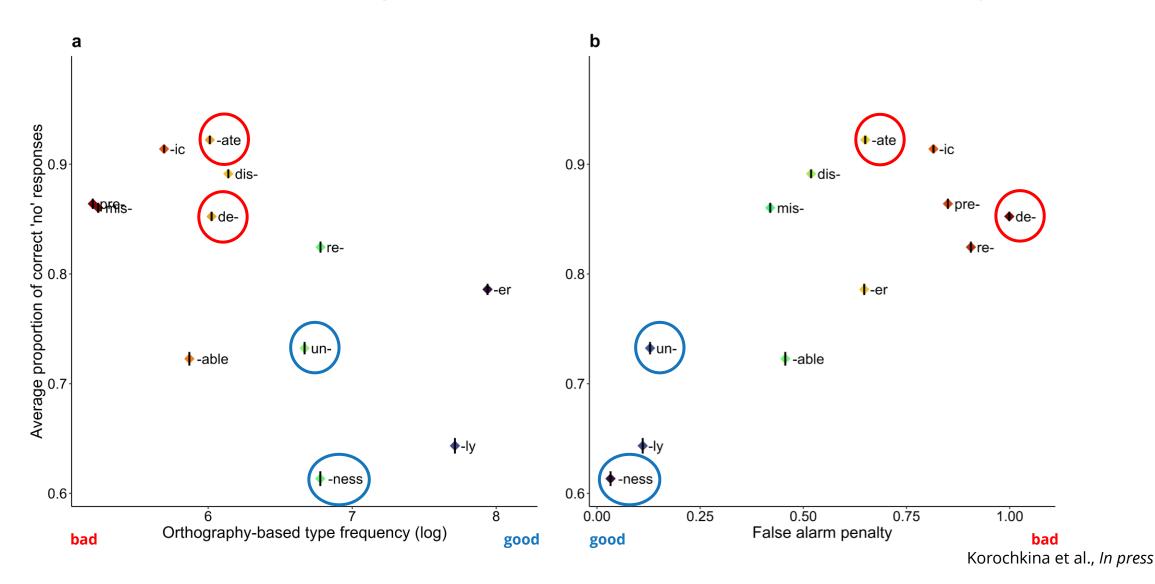
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#### Theory 3 explains data best!

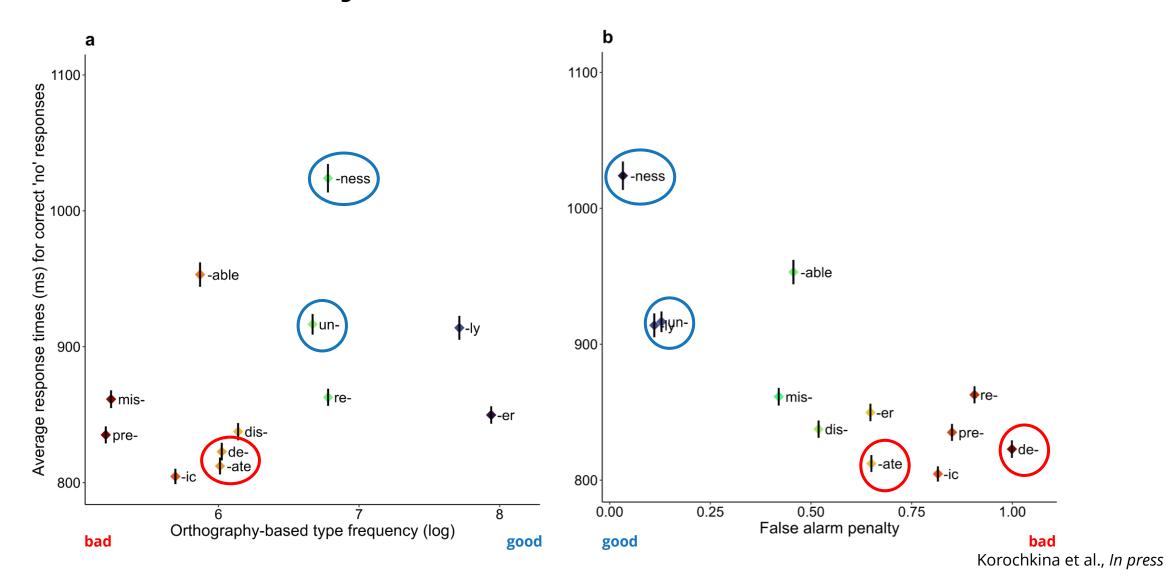


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#### Nonwords with "good" affixes are hard to reject...



#### ... and these rejections take time

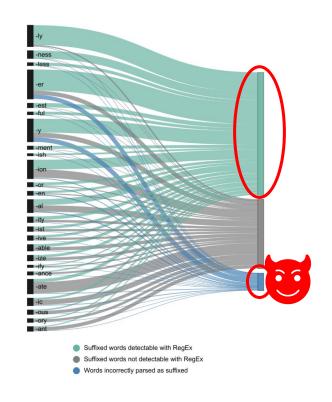


#### Interim summary

Quantified morpheme experience in print

↓
Proposed a new definition of morpheme experience

↓
Tested this definition against human data



- Critical step toward a **psychologically valid theory** of morpheme learning
- However, this approach is still a workaround: needs expert input and reduces affix meaning to a binary distinction

# Modelling affix learning

... through compositional distributional semantic models

#### Distributional semantics

- A word's meaning can be inferred from contexts in which it appears
  - Similar contexts → similar meanings
  - Distinct contexts → more divergent meanings

boat

ship

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- A word's meaning can be inferred from contexts in which it appears
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	water	passenger	sea
boat			
ship			

### Distributional semantics

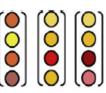
- A word's meaning can be inferred from contexts in which it appears
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	water	passenger	sea
boat	23	15	40
ship	25	20	50

• Co-occurrence matrix (e.g., LSA) / neural embeddings (e.g., word2vec)  $\rightarrow$  vector



• Collection of vectors for a large number of words – **semantic space** 



# **Compositional** distributional semantics CAOSS

snowman

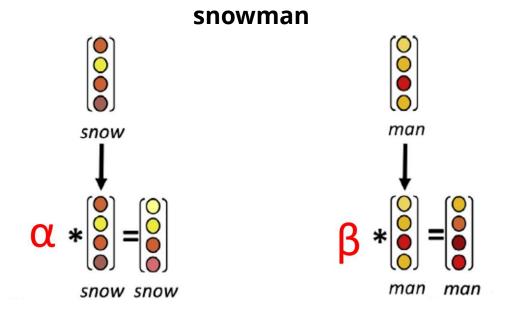
# **Compositional** distributional semantics CAOSS

#### snowman



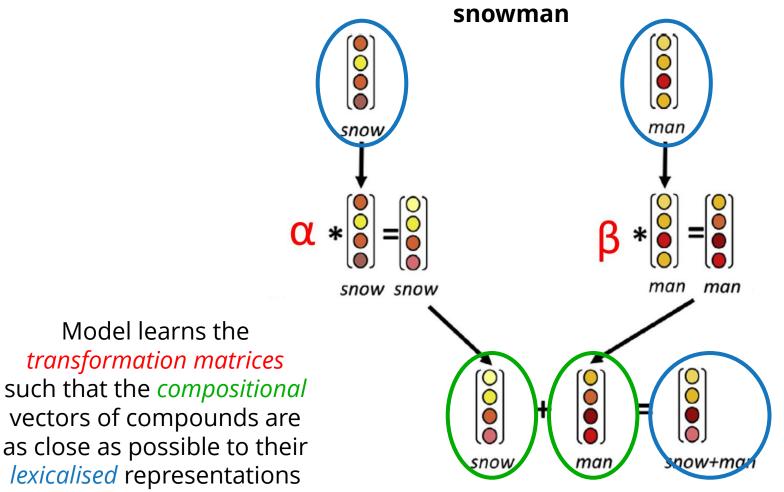


# **Compositional** distributional semantics CAOSS



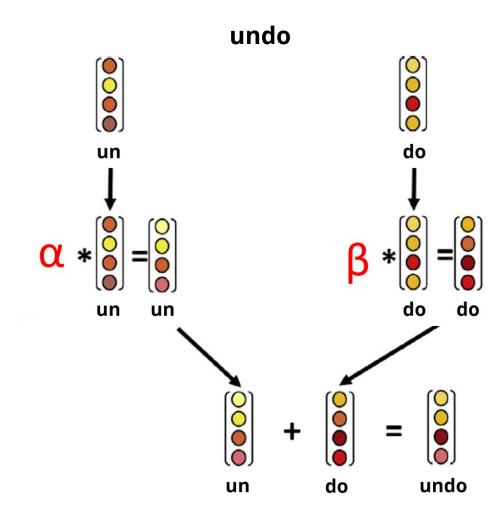
### Compositional distributional semantics **CAOSS**

Model learns the



Model receives *lexicalised* representations of stems and compounds

## CAOSS applied to affixation



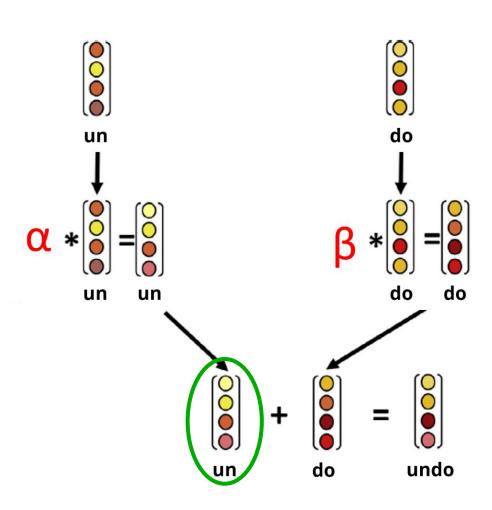
### Our modelling approach

## Lexicalised representations

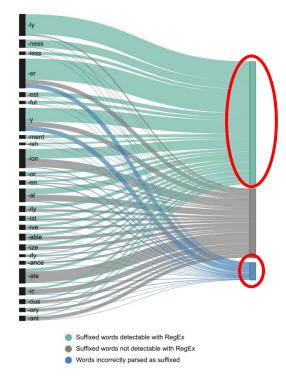
for words & affixed words from *subs2vec* (van Paridon & Thompson, 2021)

#### **Affix representations**

Average of vector representations of all words with this affix (Westbury & Hollis, 2019)



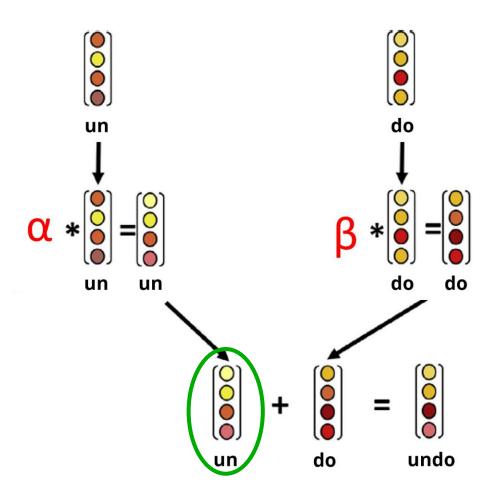
#### **Training set**



#### **CAOSS** metrics

Does model knowledge of affixes account for patterns in human lexical processing?

Morpheme interference data from Korochkina et al., *In press* 



#### **Affix diffuseness**

Degree of diffusion and uncertainty in the affix meaning

#### **Affix richness**

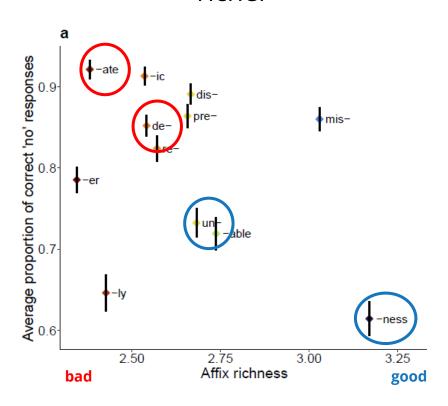
Richness and complexity of affix meaning

#### **Affix coherence**

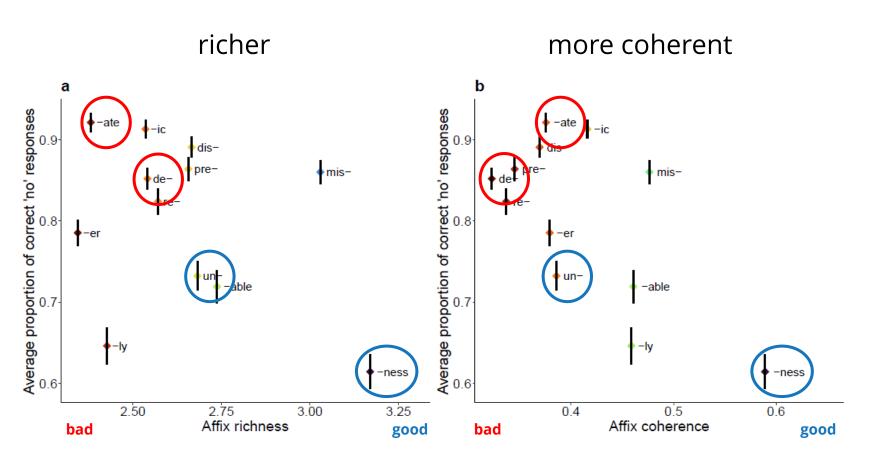
Similarity between the meaning of the affix and the meanings of words that contain it

## More errors when rejecting nonwords with affixes with...

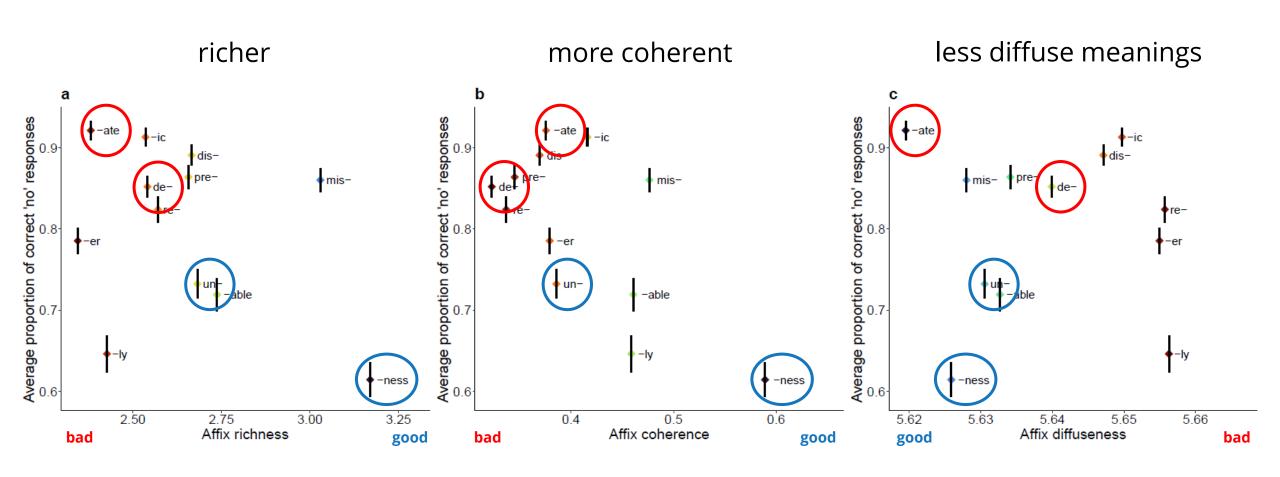
richer



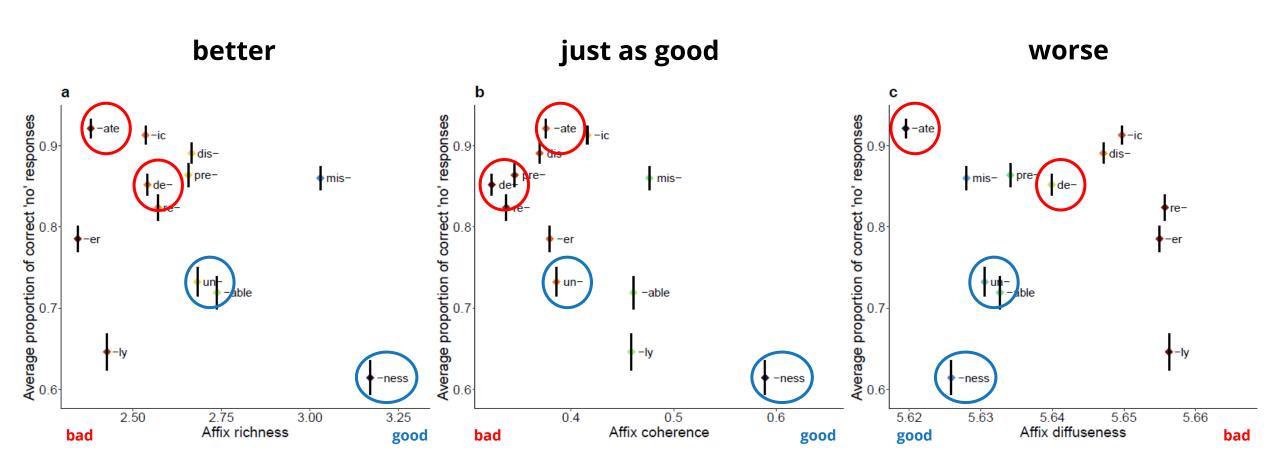
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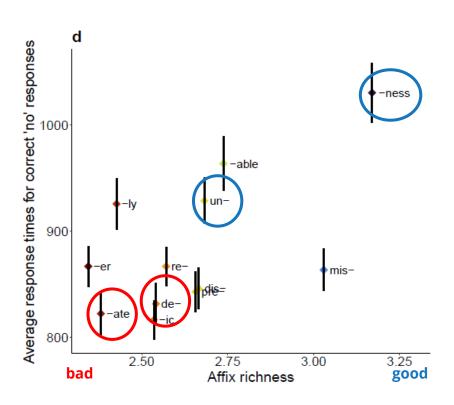


## Compared to the false alarm penalty model...

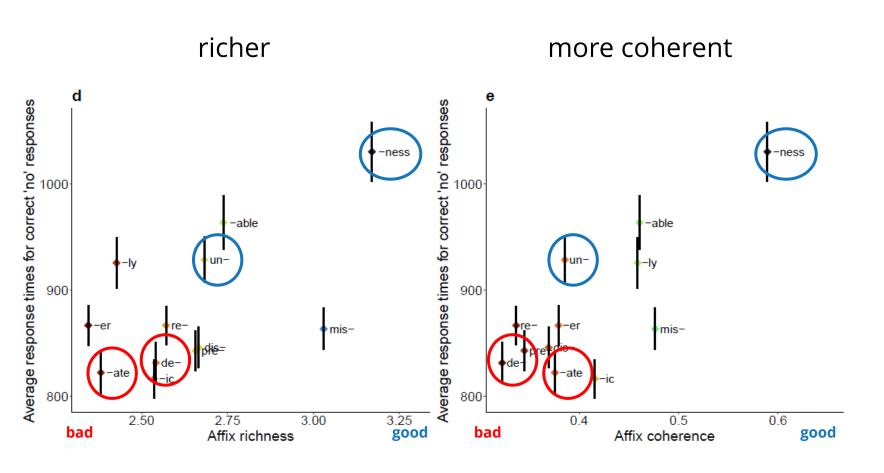


# Slower when rejecting nonwords with affixes with...

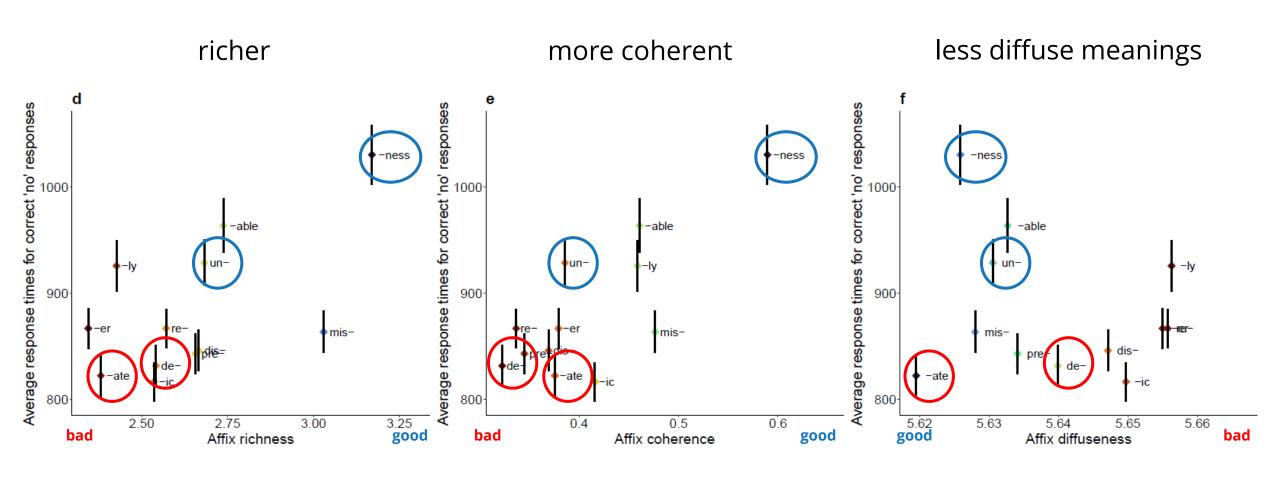
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# Slower when rejecting nonwords with affixes with...



## Slower when rejecting nonwords with affixes with...



## Compared to the false alarm penalty model...



### Recall our interim summary...

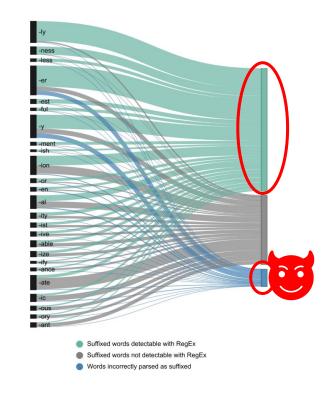
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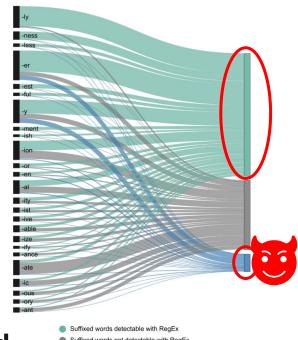
- Critical step toward a **psychologically valid theory** of morpheme learning
- However, this approach is still a workaround: needs expert input and reduces affix meaning to a binary distinction

### Conclusions

Quantified morpheme experience in print

Proposed a new definition of morpheme experience

Tested this definition against human data



- Principled, scalable account of morpheme learning in the wild
- Innovation in computational modelling of affix semantics
  - First use of CAOSS with "noisy" input
  - First attempt to model prefix semantics

Readers' text experience shapes perception of both affix meaningfulness and plausibility of novel morphemic combinations

## Further reading

Article Open access Published: 05 May 2025

### Morphology in children's books, and what it means for learning

npj Science of Learning 10, Article number: 22 (2025) Cite this article

4985 Accesses 23 Altmetric Metrics

https://doi.org/10.1038/s41539-025-00313-6



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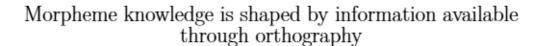
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Maria Korochkina 1, Holly Cooper 1, Marc Brysbaert 2, and Kathleen  ${\bf Rastle}^1$ 

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#### https://doi.org/10.1038/s41539-025-00313-6

Morpheme knowledge is shaped by information available through orthography

Maria Korochkina<sup>1</sup>, Holly Cooper<sup>1</sup>, Marc Brysbaert<sup>2</sup>, and Kathleen Rastle<sup>1</sup>

In press in *Psychon. Bul. Rev.*, pre-print at:

https://doi.org/10.31219/osf.io/ad3jh\_v2



Morphemes in the wild: Modelling affix learning from the noisy landscape of natural text

Maria Korochkina<sup>1</sup>, Marco Marelli<sup>2</sup>, and Kathleen Rastle<sup>1</sup>

Under review, pre-print at:

https://doi.org/10.31234/osf.io/yzcqm\_v1













Holly Cooper Marco Marelli

Marc Brysbaert Kathy Rastle

## Thank you!

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### Additional slides

Nonword-based metrics

### Role of stem-affix combination

3 nonword-based metrics

- Nonword diffuseness: how well-defined or vague a nonword's meaning is
- Nonword richness: semantic richness of a nonword's meaning
- Nonword neighbourhood density: proximity of a nonword to its nearest semantic neighbours
- → Does the inclusion of these metrics into the models with affix-based metrics improve model fit?

### Role of stem-affix combination

#### 3 nonword-based metrics

- Nonword diffuseness: how well-defined or vague a nonword's meaning is
- Nonword richness: semantic richness of a nonword's meaning

Yes, for the affix richness (accuracy only) and affix diffuseness models

 Nonword neighbourhood density: proximity of a nonword to its nearest semantic neighbours
 Yes, for all response

es, for all response times models

→ Does the inclusion of these metrics into the models with affix-based metrics improve model fit?

### Summing up

- Morphologically structured nonwords most difficult to reject when...
  - they are semantically rich,
  - closely related in meaning to their semantic neighbours,
  - contain affixes with richer, more coherent, and less diffuse meanings

- Affix meaningfulness influenced processing more than the overall nonword meaning
- Skilled readers' judgments of affixed nonwords are driven mainly by the properties
  of the affixes they contain, rather than by the specific meaning of the stem-affix
  combination in each individual nonword