

Are formal restrictions on crossing dependencies epiphenomenal?

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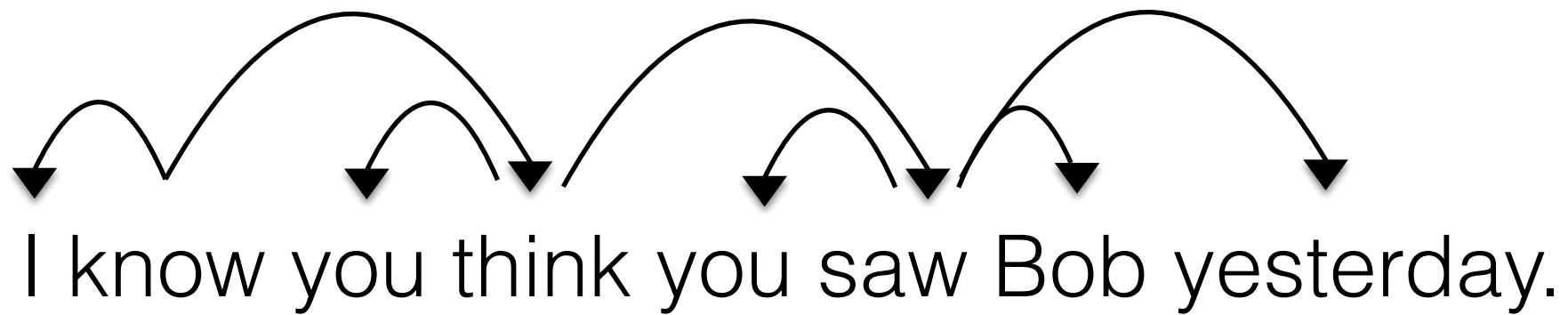
Richard Futrell*

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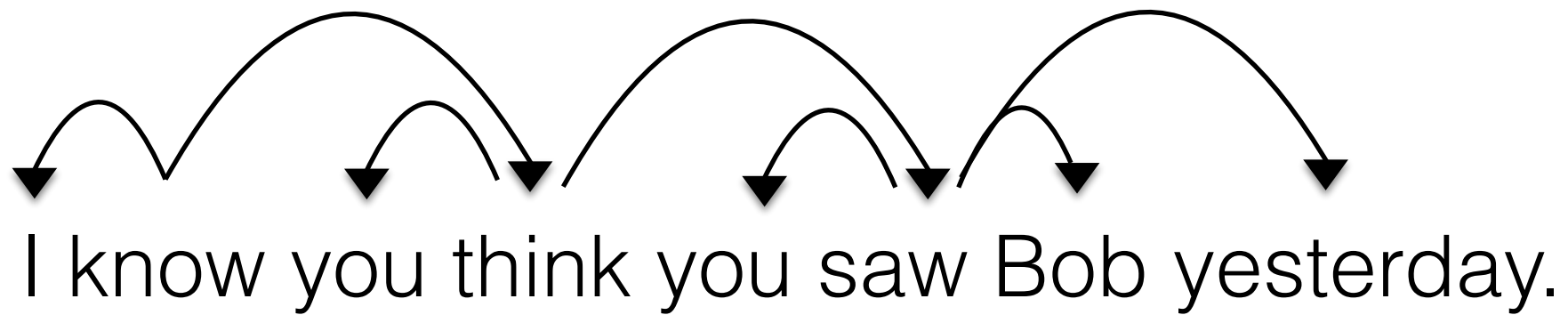
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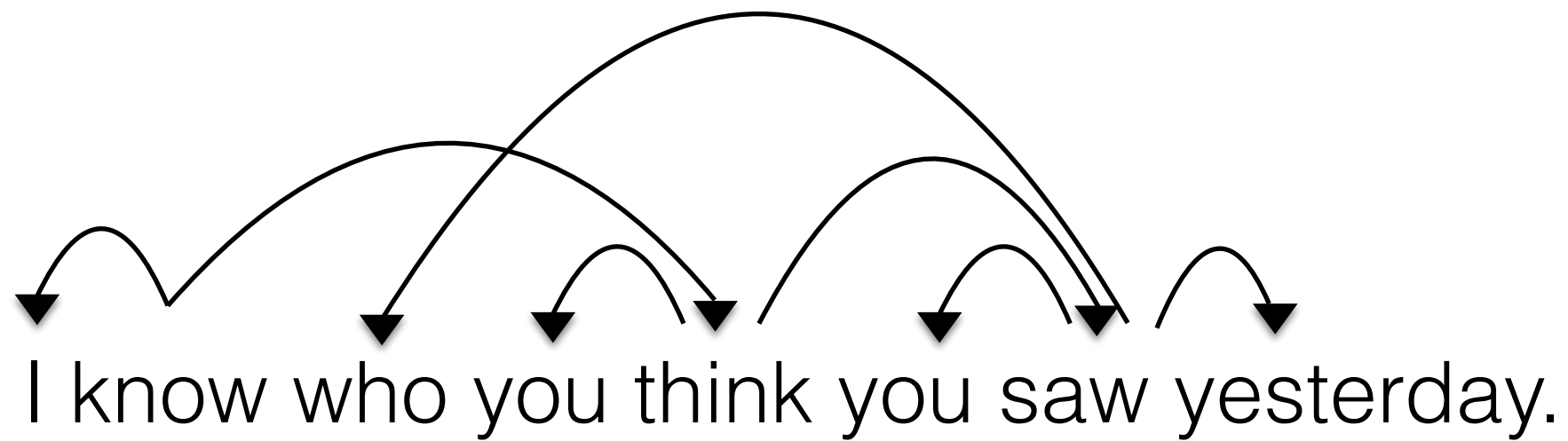


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(that is, the lines don't cross)

But sometimes they're not



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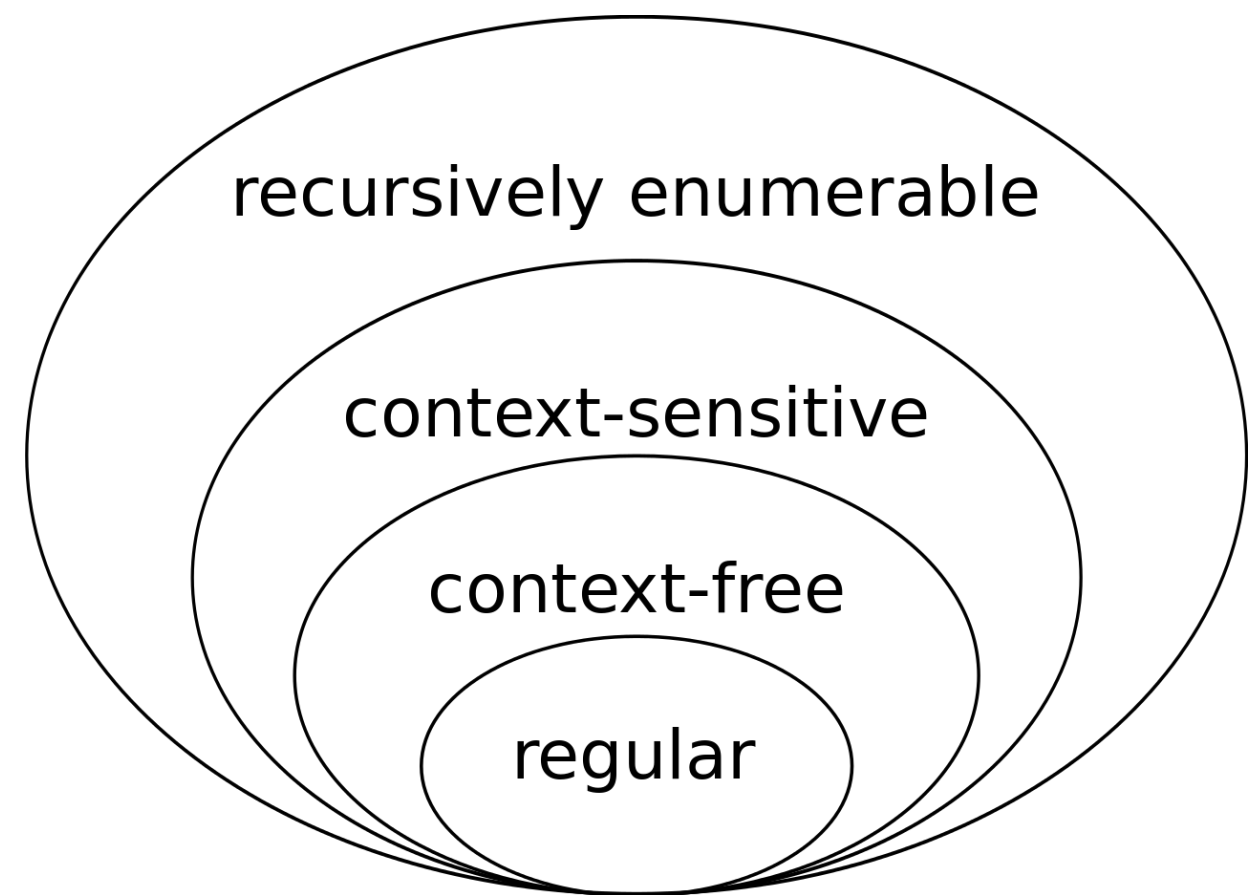
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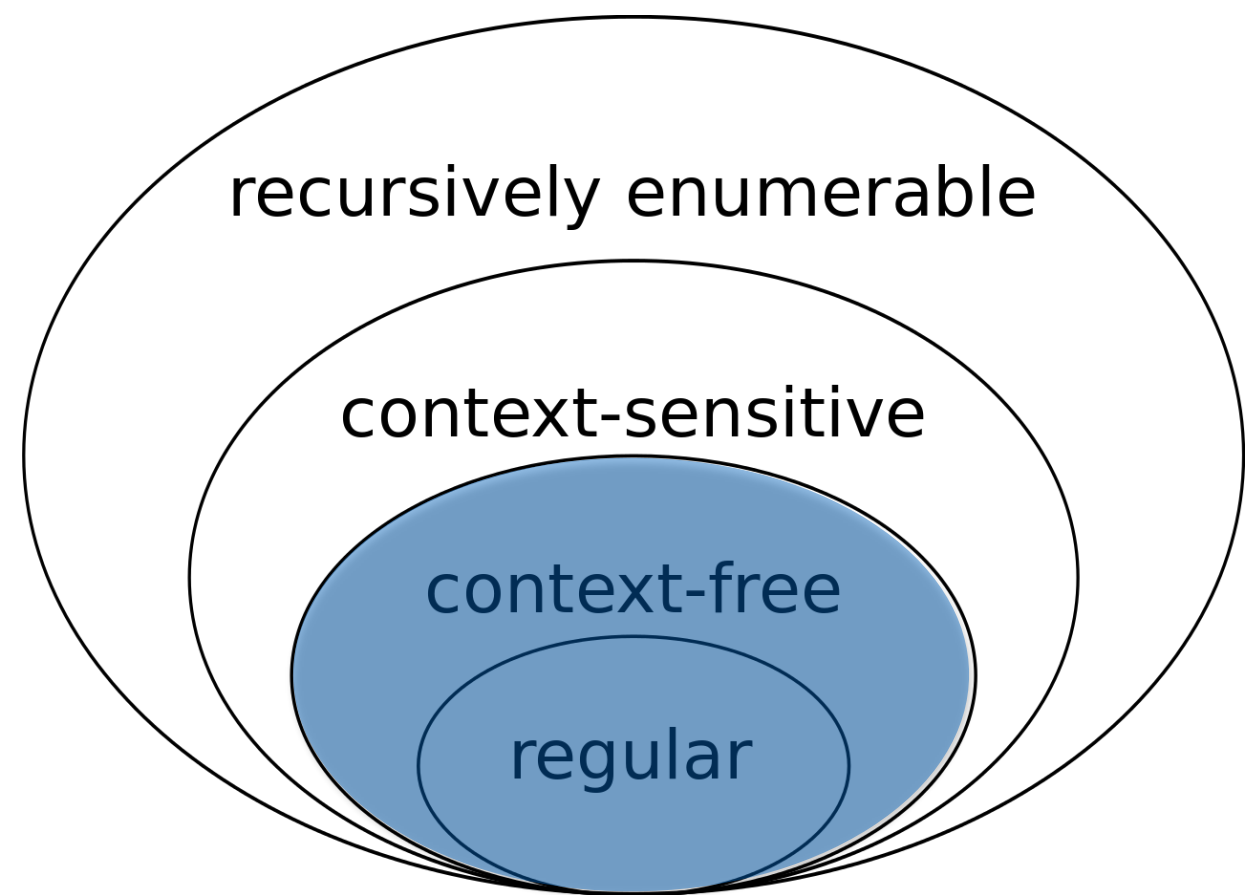
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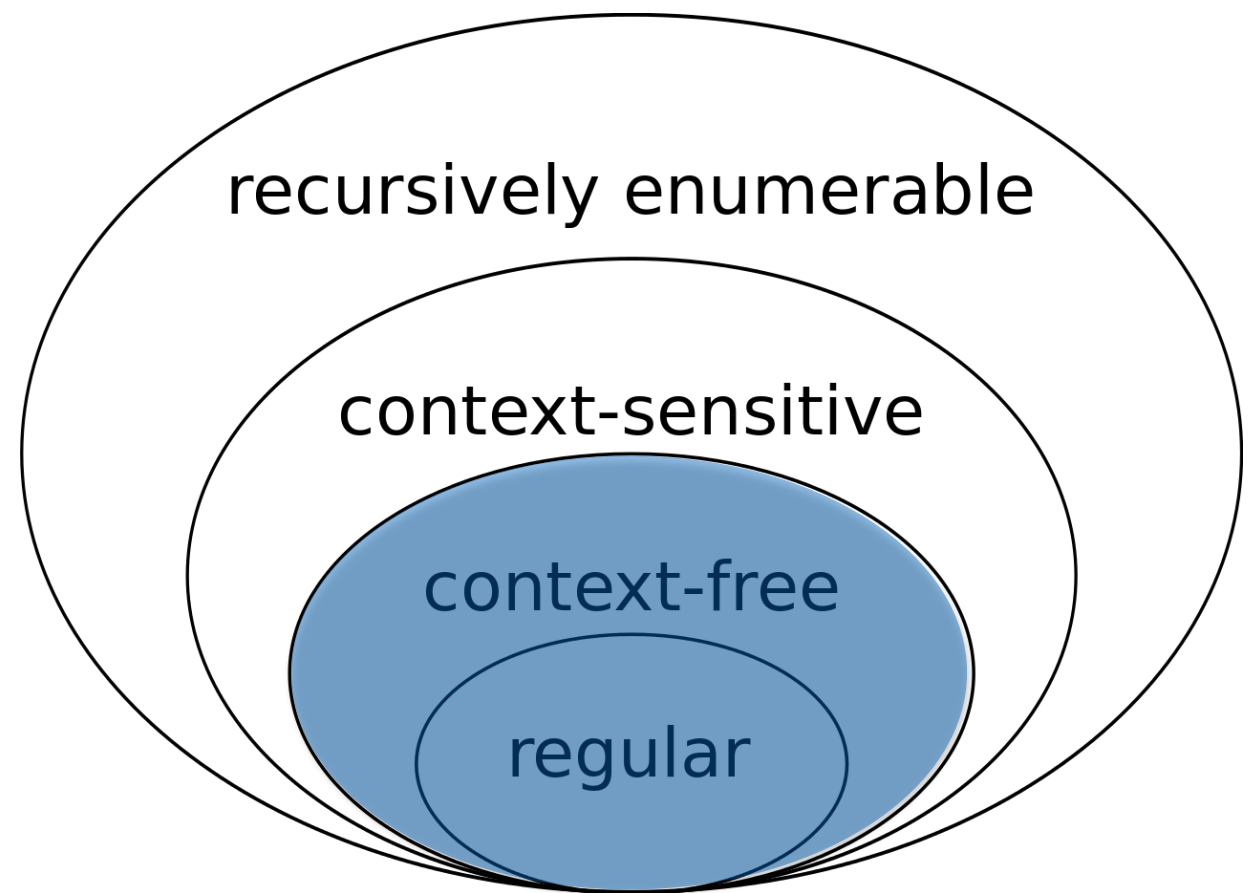
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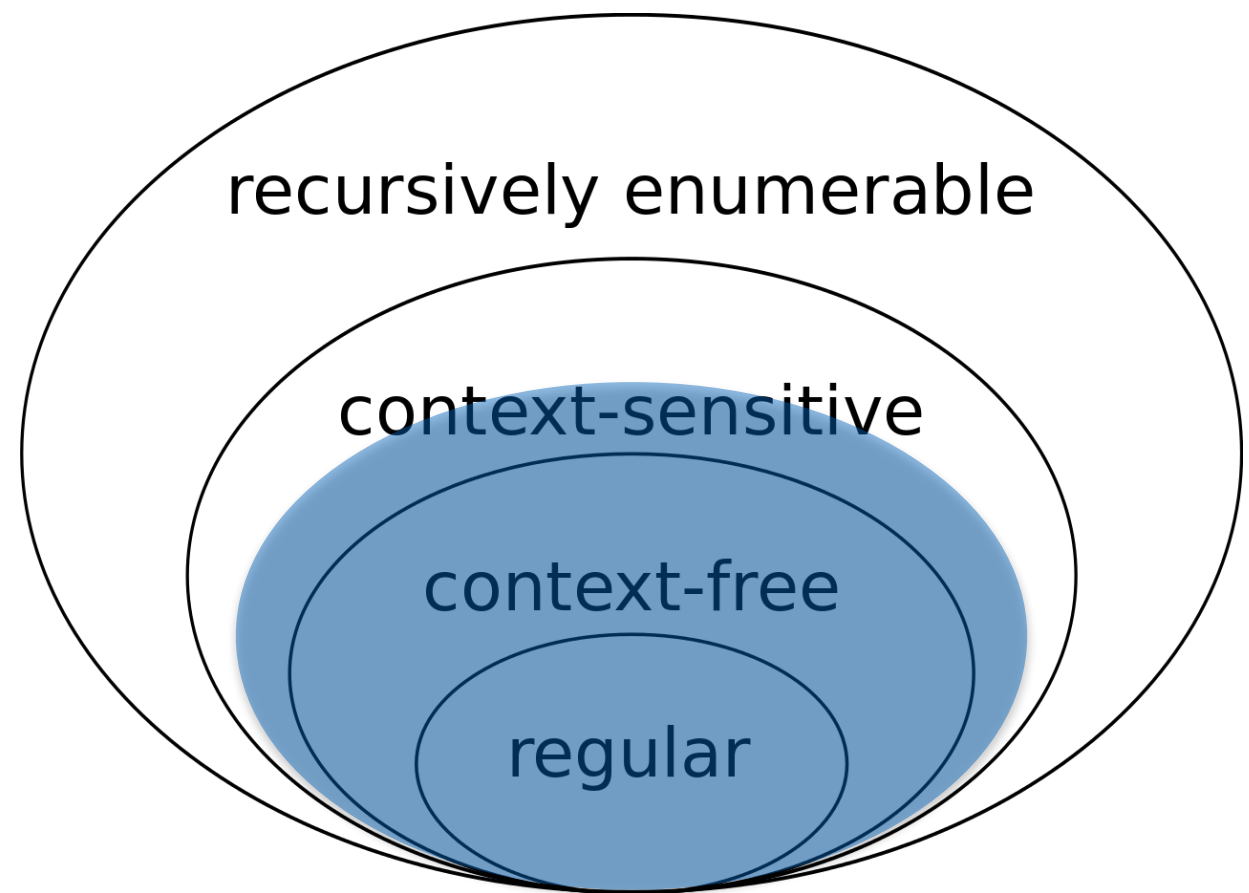
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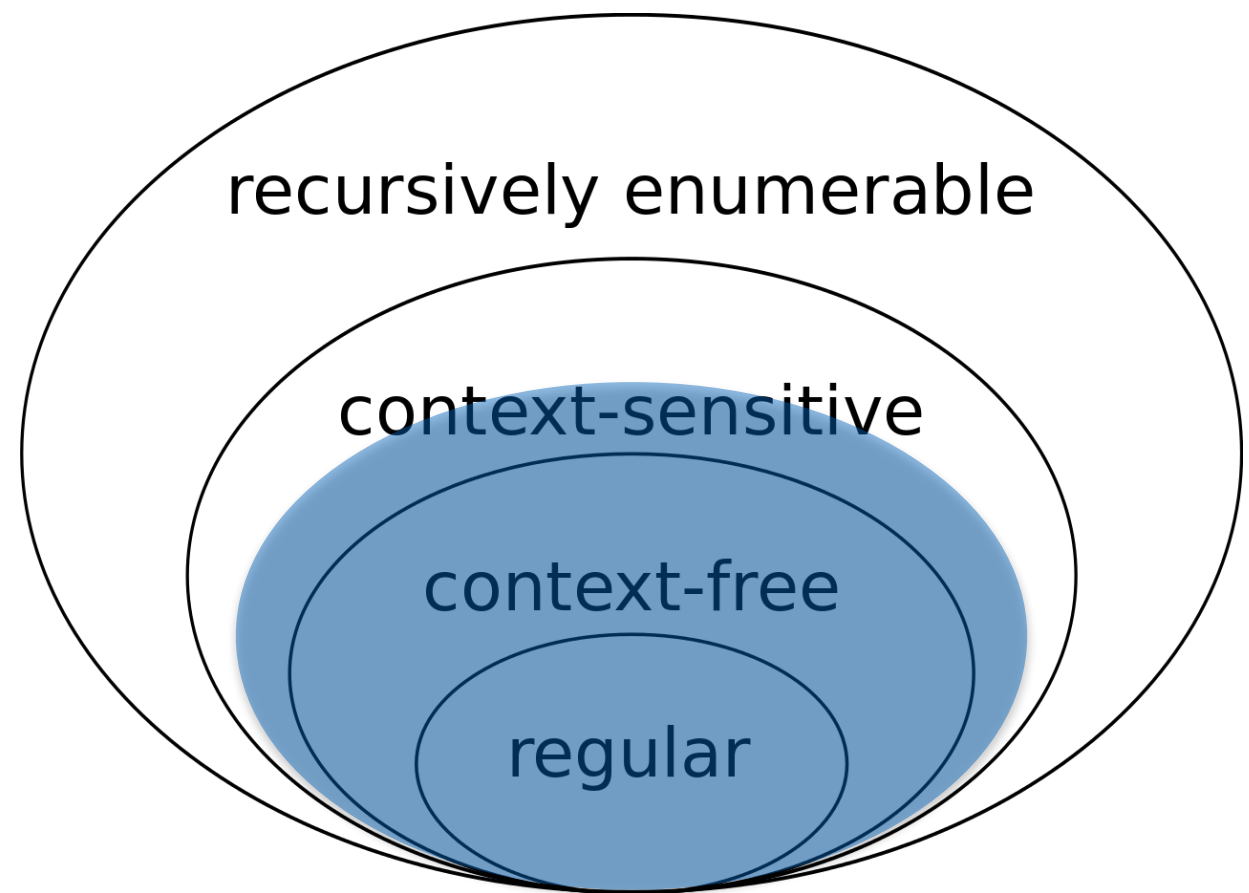
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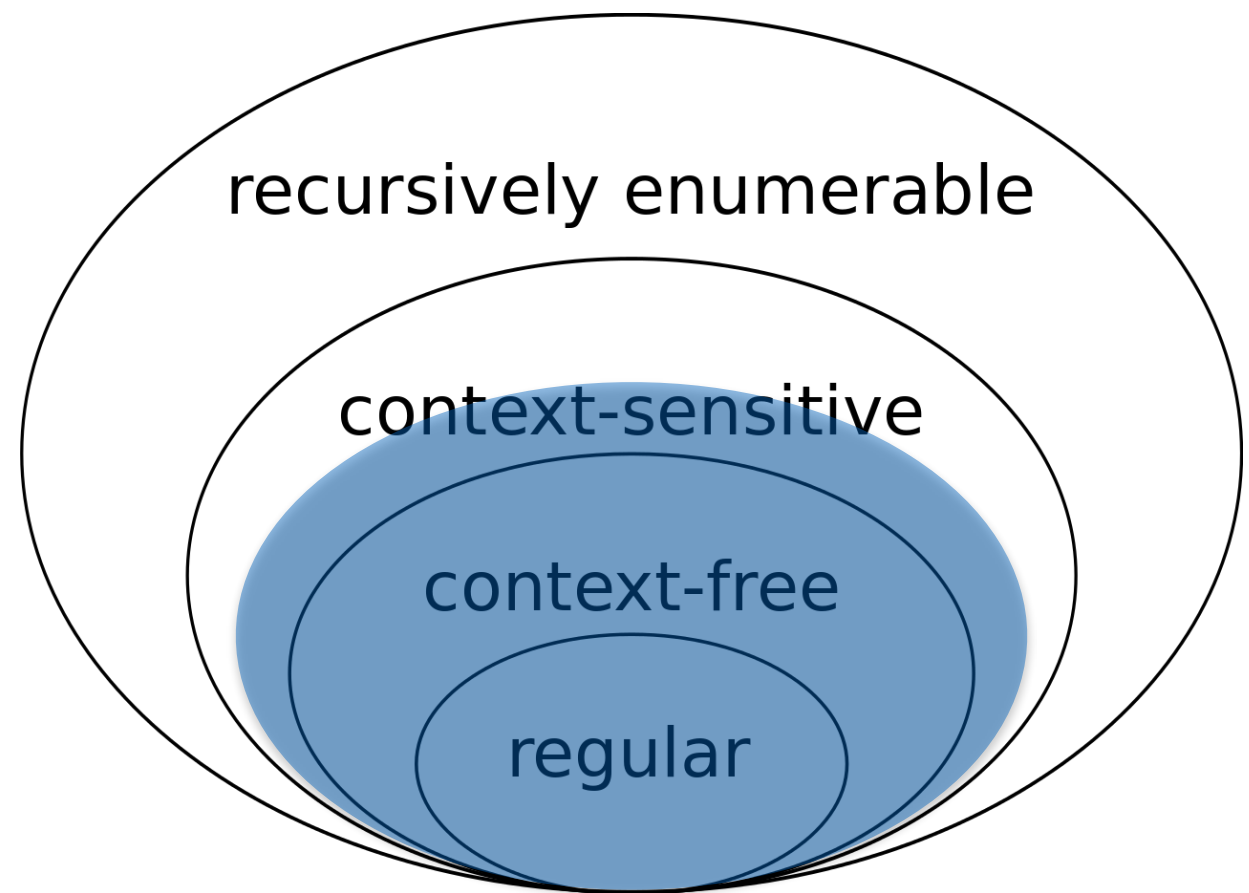
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- The **mildly context-sensitive languages** are defined by **bounds on gap degree**.



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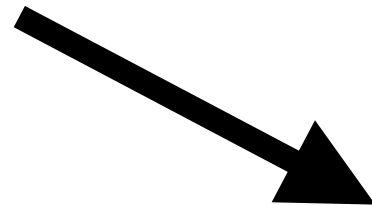
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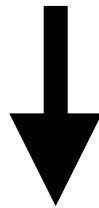
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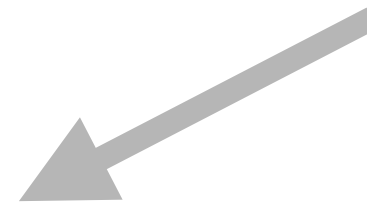
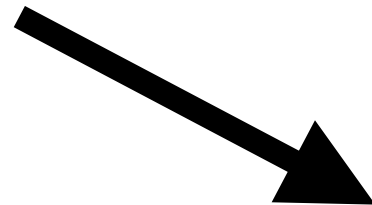
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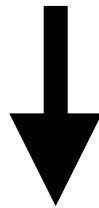
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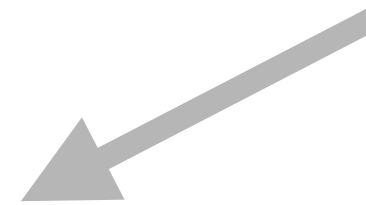
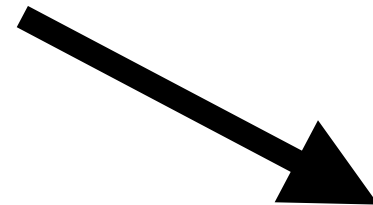


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 - We only ask **if a low rate of crossings is sufficient to explain the formal crossing constraints.**

Are crossing constraints epiphenomenal?

- Introduction
- Methodology & Baselines
- Results
- Conclusion

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- **Random trees**: Uniform random trees generated using Prüfer codes, with the same distribution over sentence lengths as real trees.

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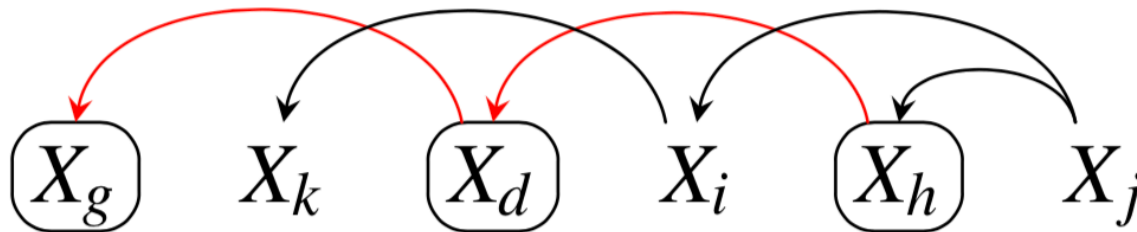
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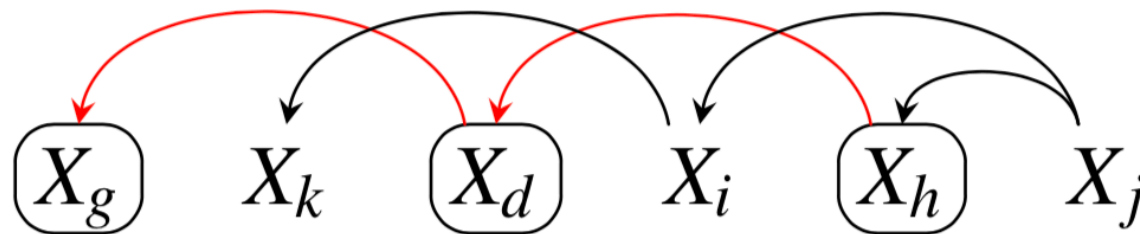
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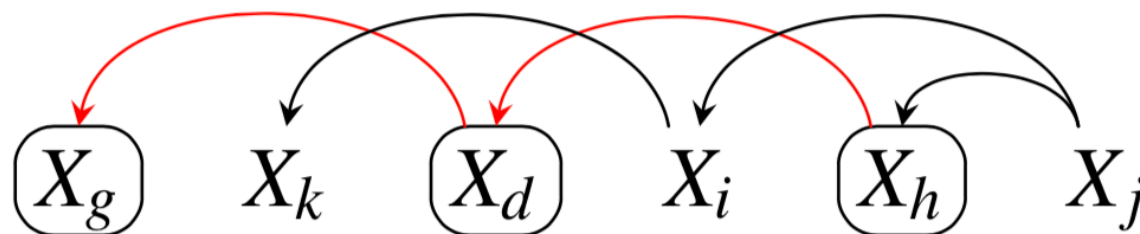
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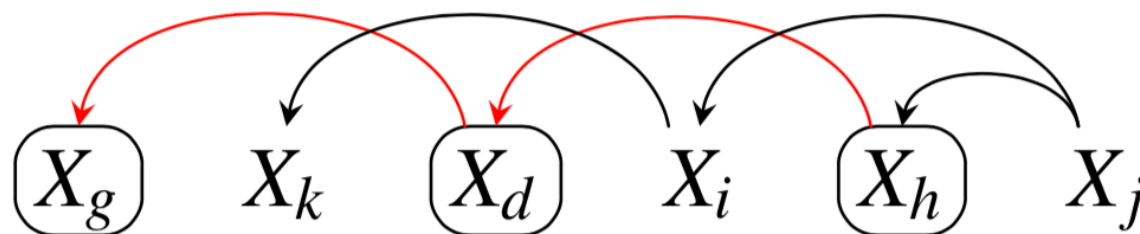


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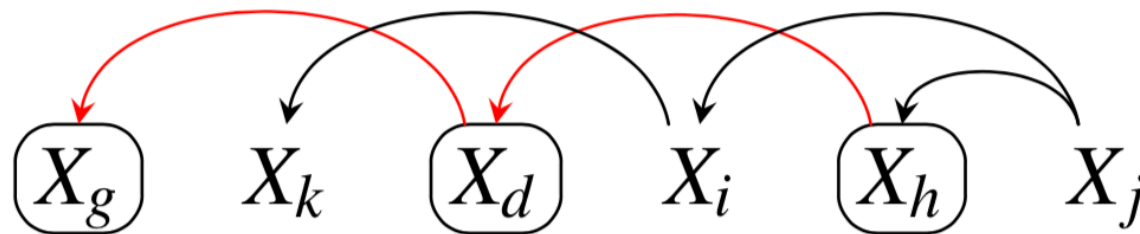


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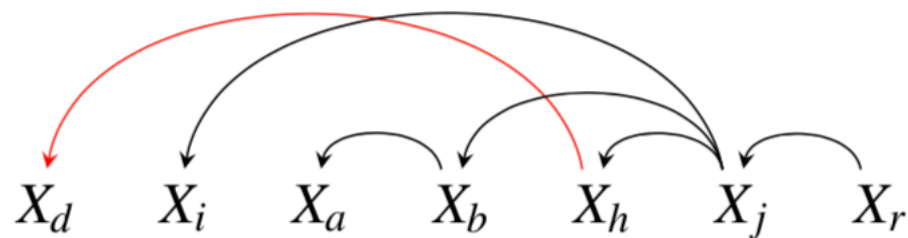
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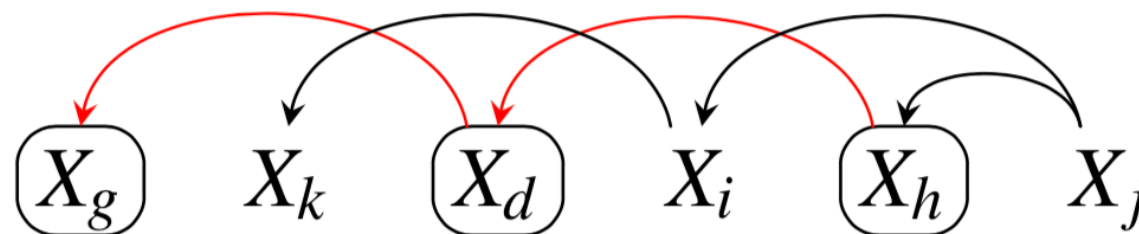
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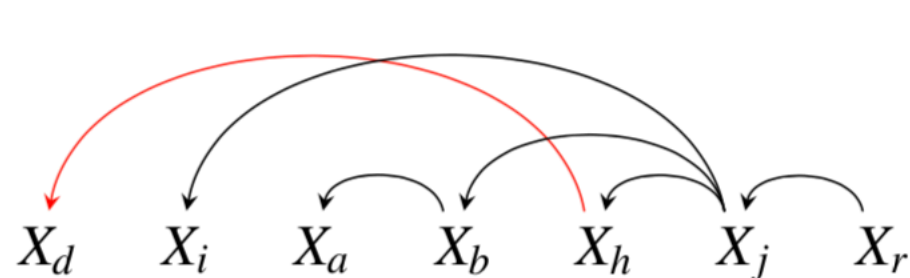
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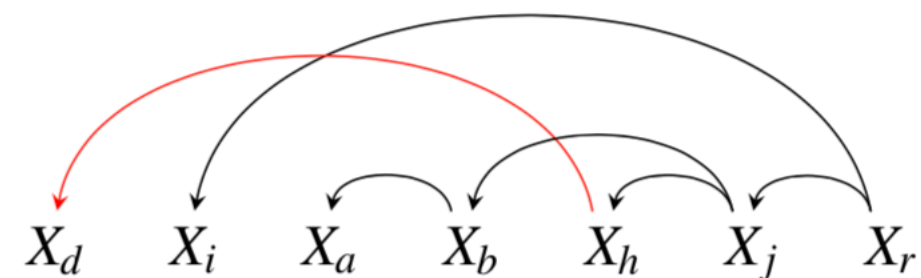


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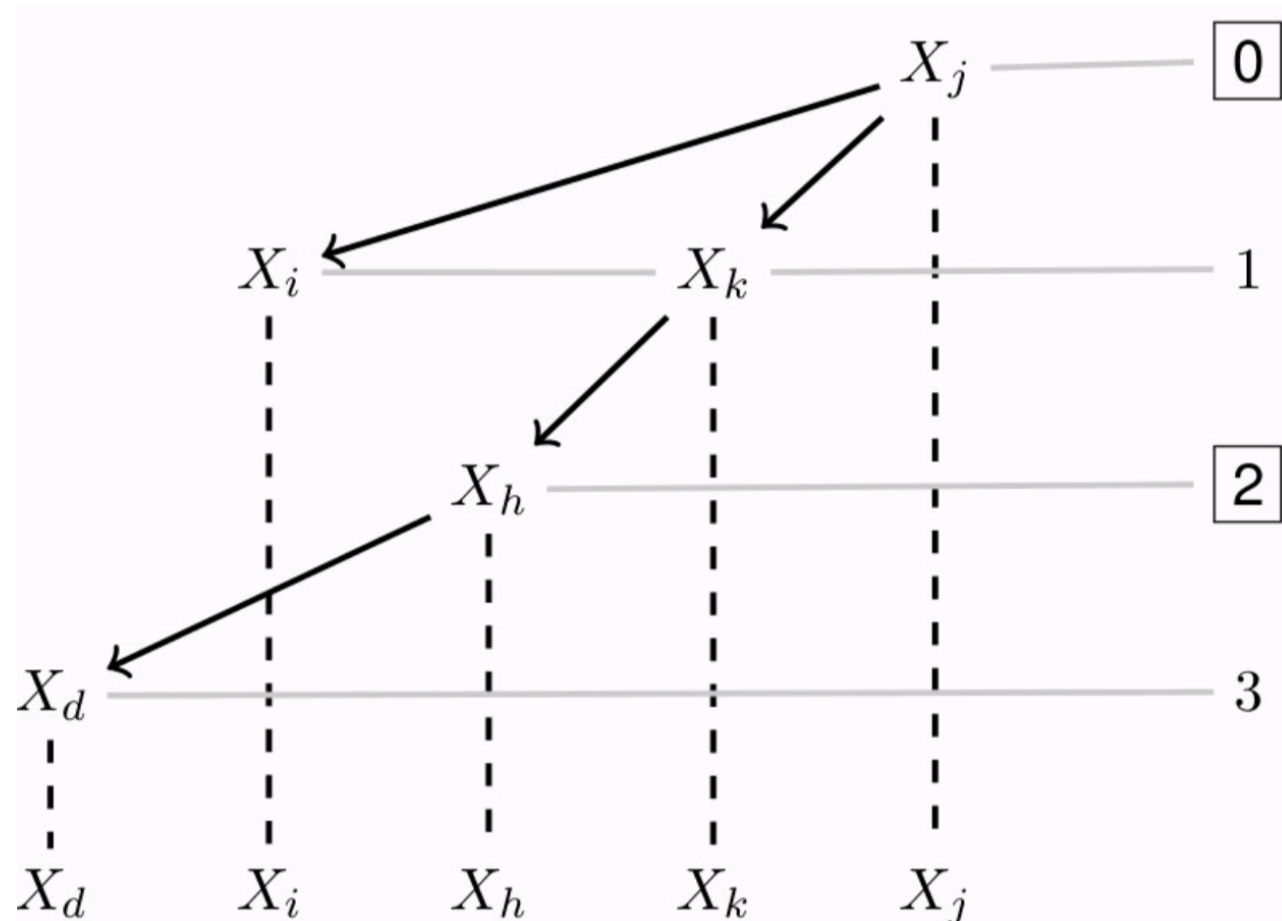
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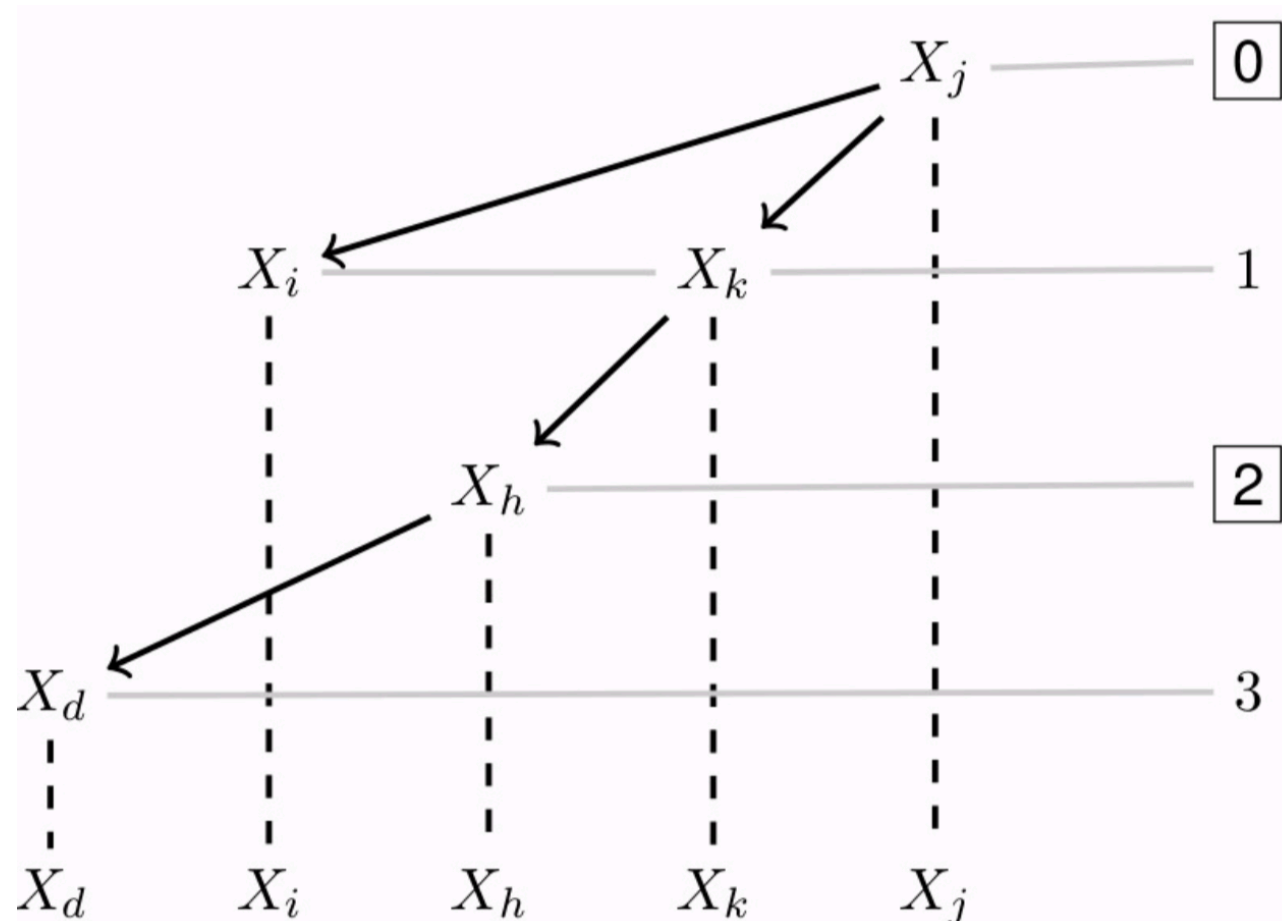
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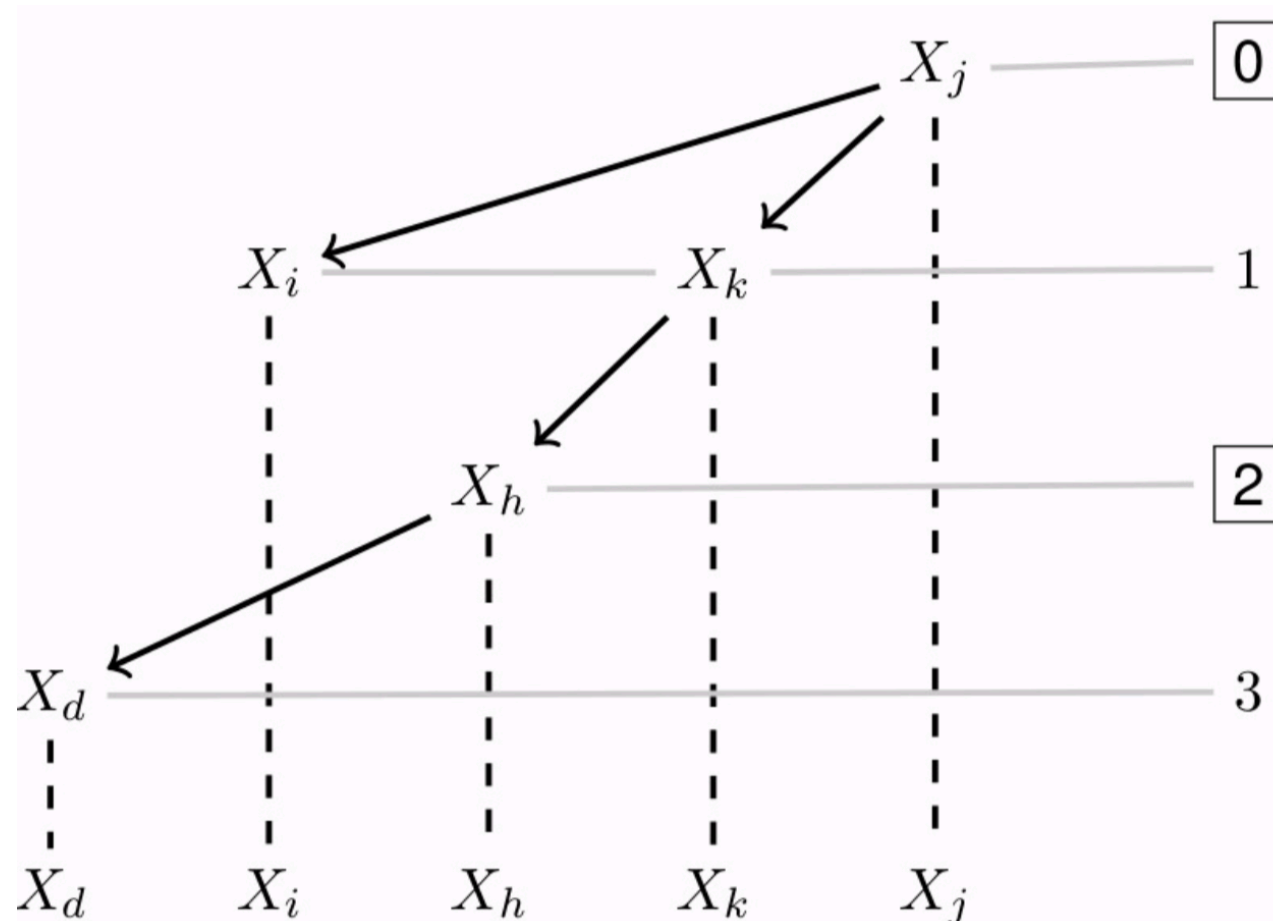
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- HDD is implicated in human processing difficulty (Phillips et al., 2005; Yadav et al., 2017)

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$$\log E[g_i] = \beta_0 + \beta_l |s_i| + \beta_r r_i + \beta_{lr} r_i |s_i| + \gamma_j + \varepsilon,$$

- Where g_i is the gap degree of the i 'th sentence,
- $|s_i|$ is the length of the i 'th sentence,
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 - The important coefficient is β_{lr} , the **interaction coefficient**:
 - If it is negative, that means **gap degree grows slower with sentence length in real vs. random trees.**

Data

- We test on UD v2.3 treebanks of 14 languages:
 - German, English, Hindi, French, Arabic, Russian, Czech, Italian, Spanish, Afrikaans, Japanese, Korean, Bulgarian, Slovak
- We exclude all root and punctuation dependencies.
- We combine trees from all treebanks (but control for language in our regression models).

Are crossing constraints epiphenomenal?

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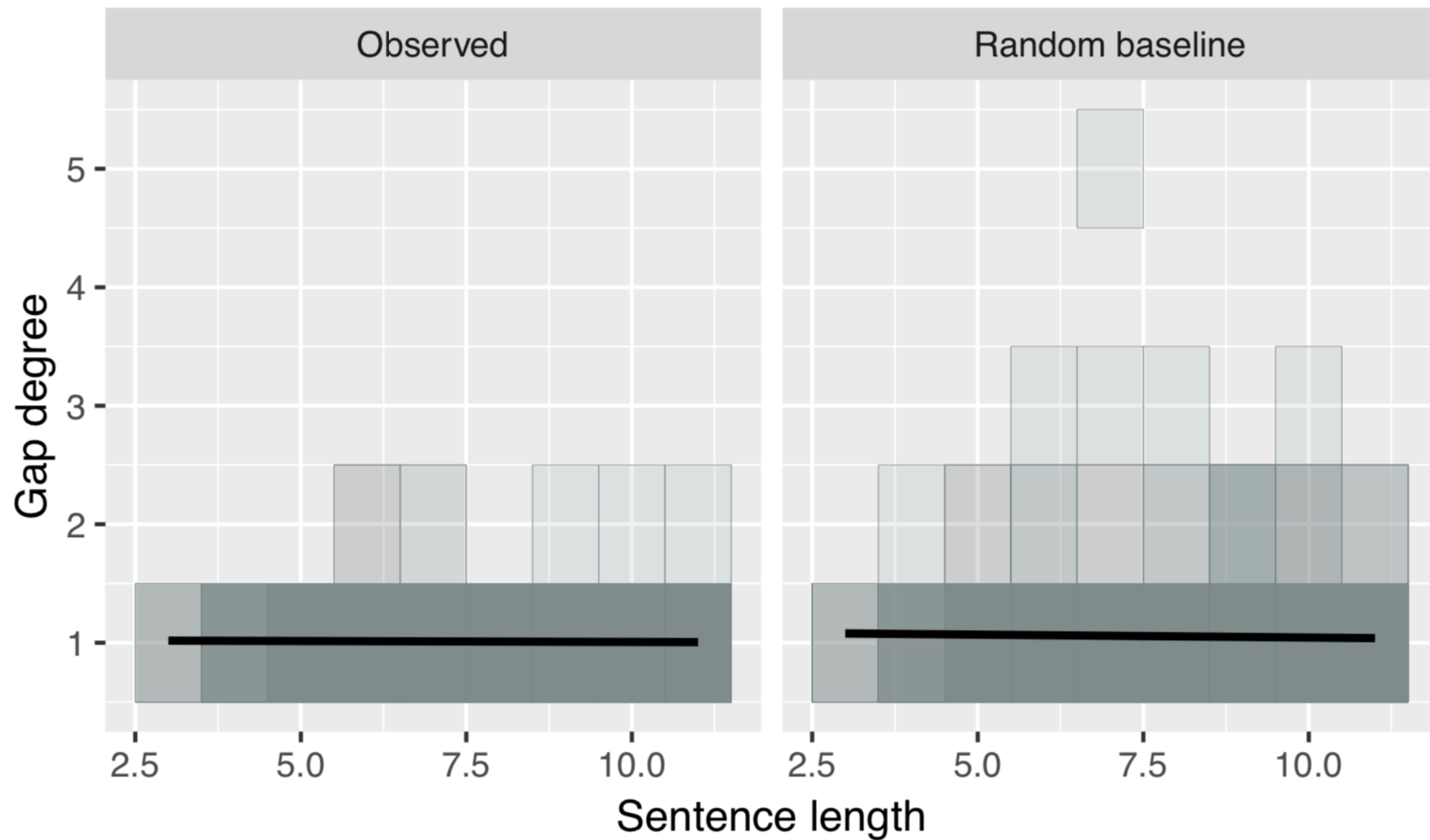
Gap Degree

Gap Degree

- As a function of **sentence length**:

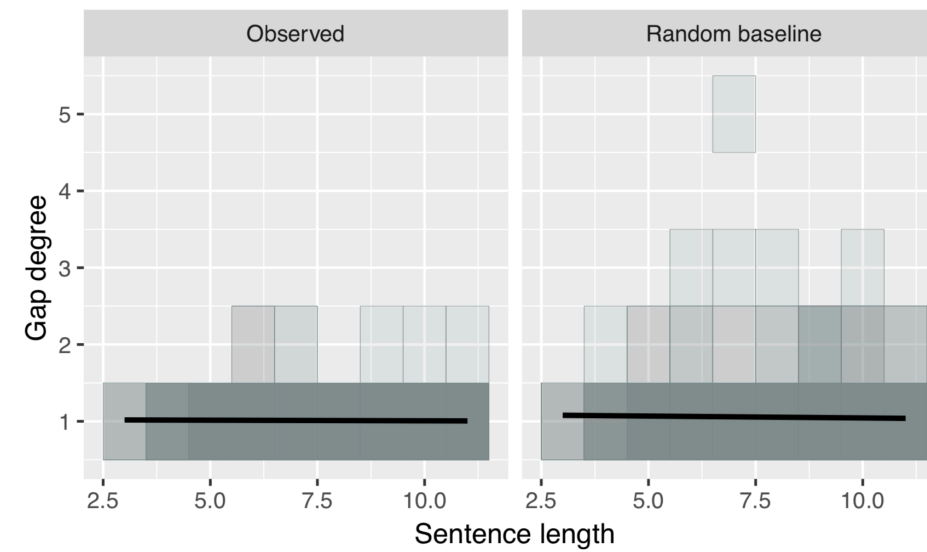
Gap Degree

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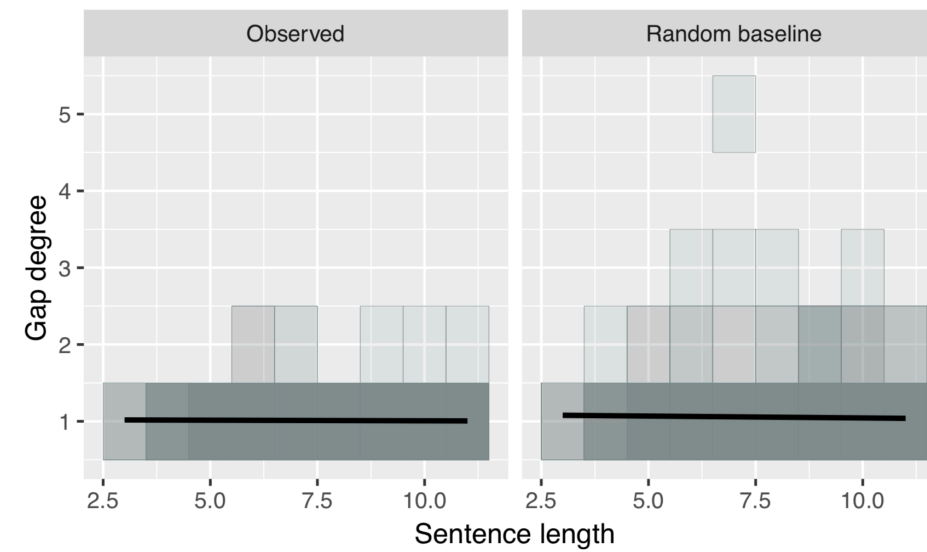
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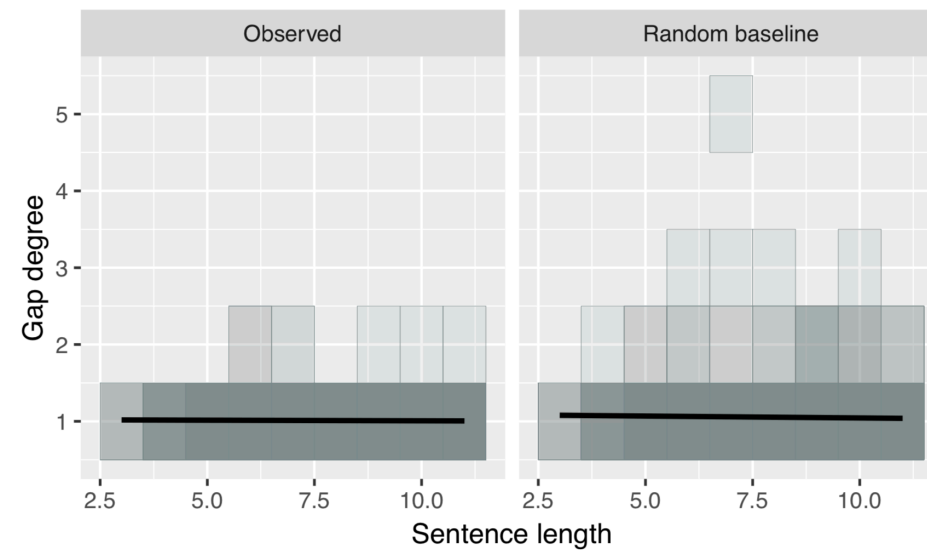
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n.s.

Gap Degree

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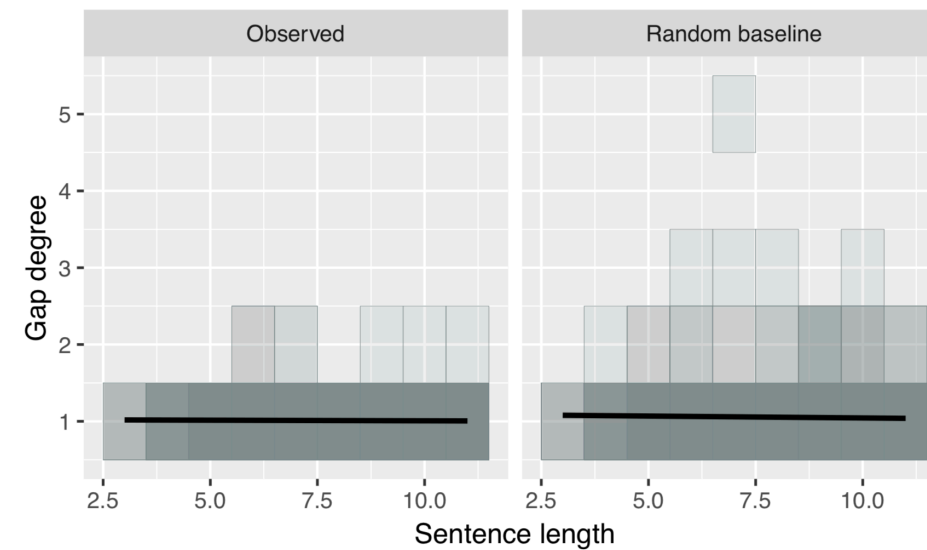


n.s.

- As a function of **tree depth**:

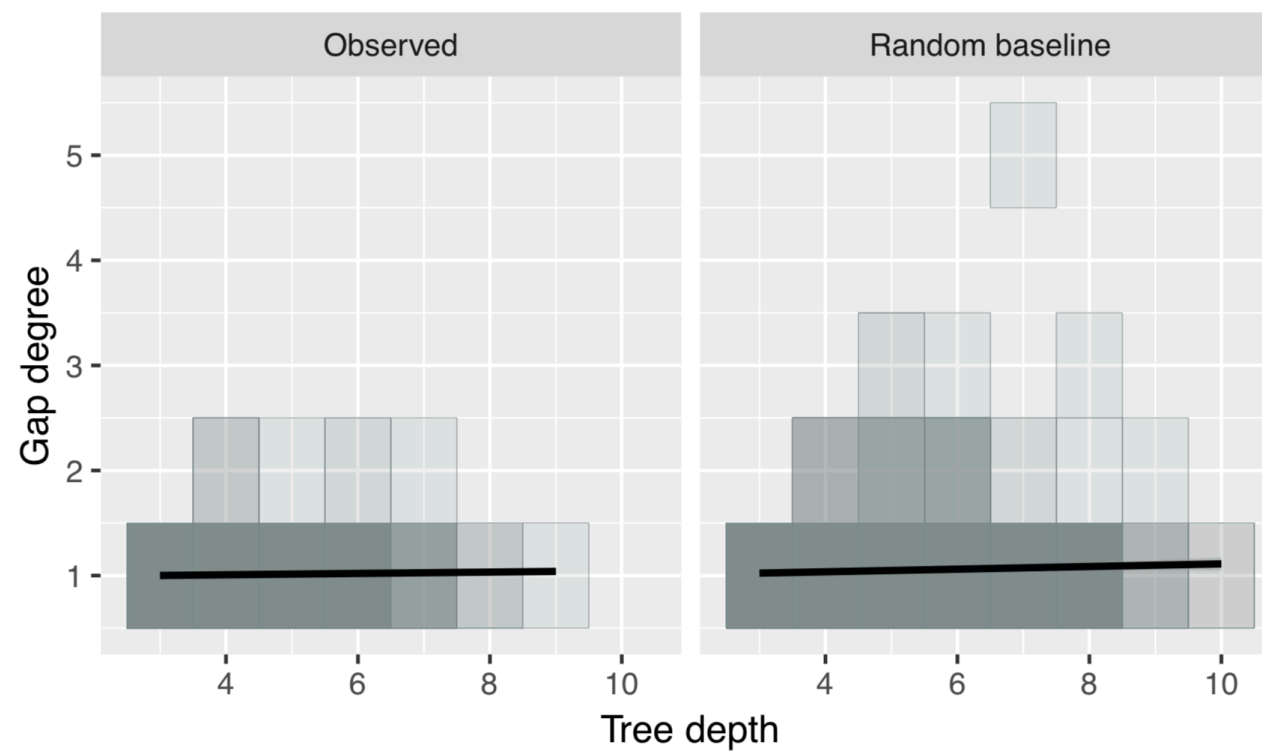
Gap Degree

- As a function of **sentence length**:



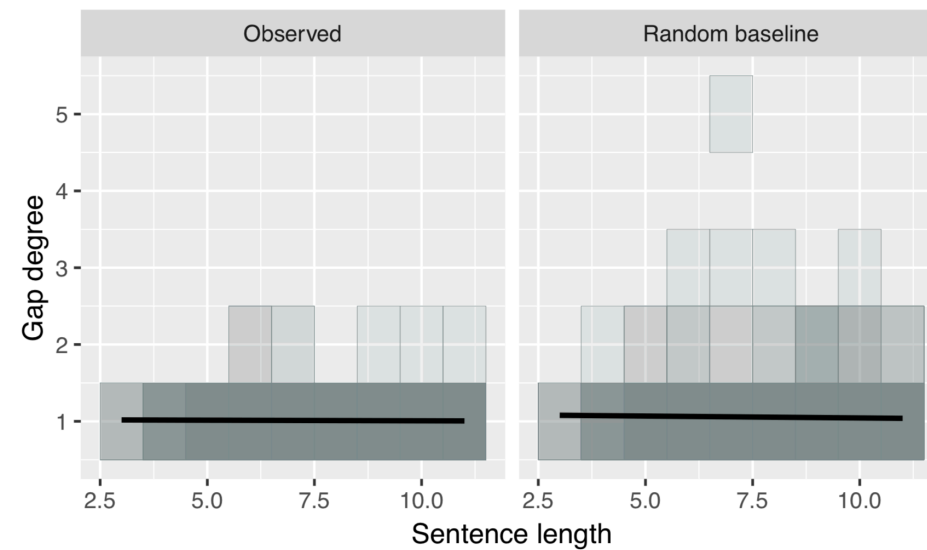
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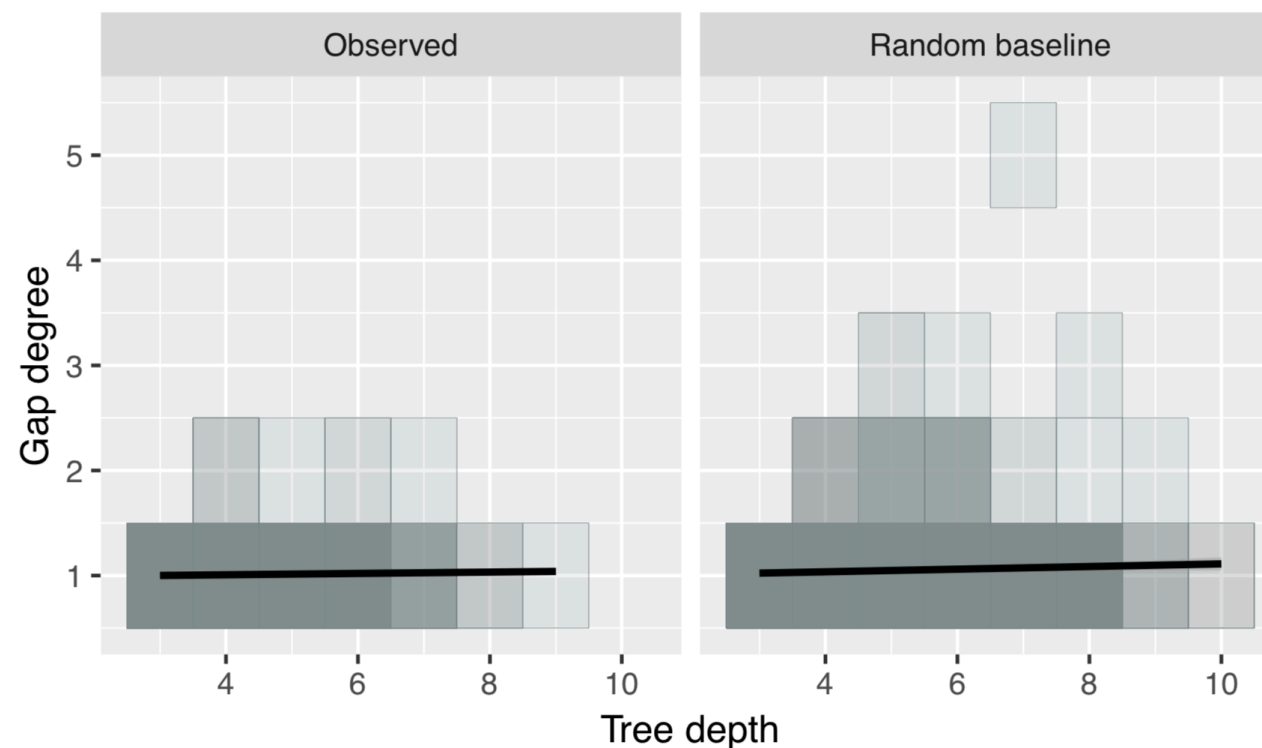
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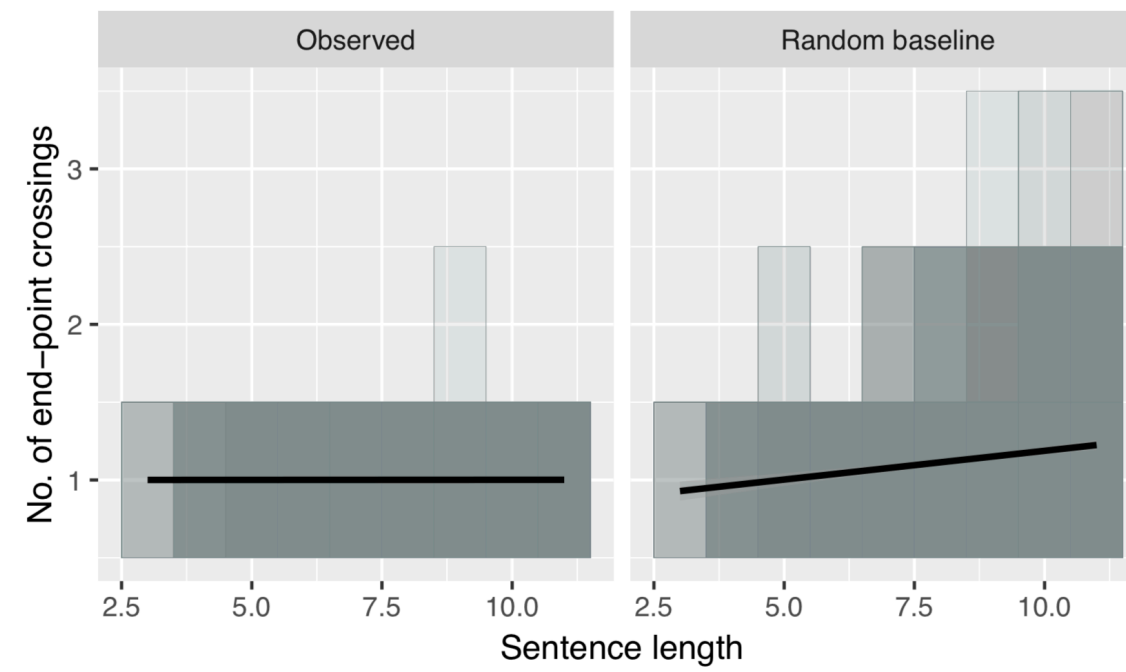
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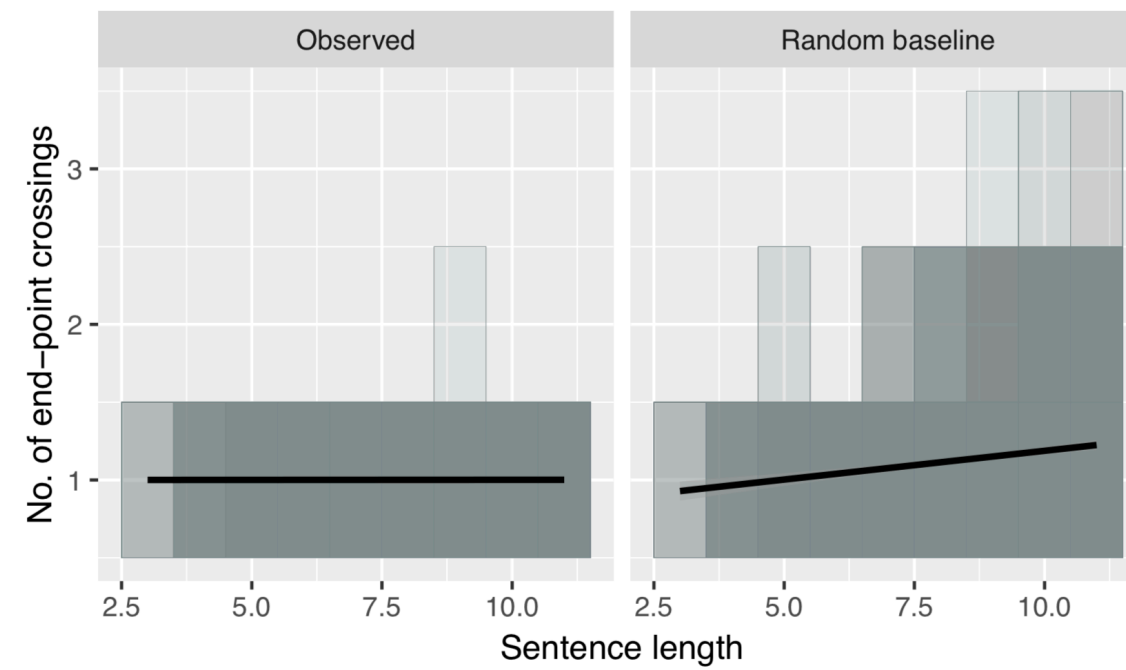
$p < .001$

End-point Crossings

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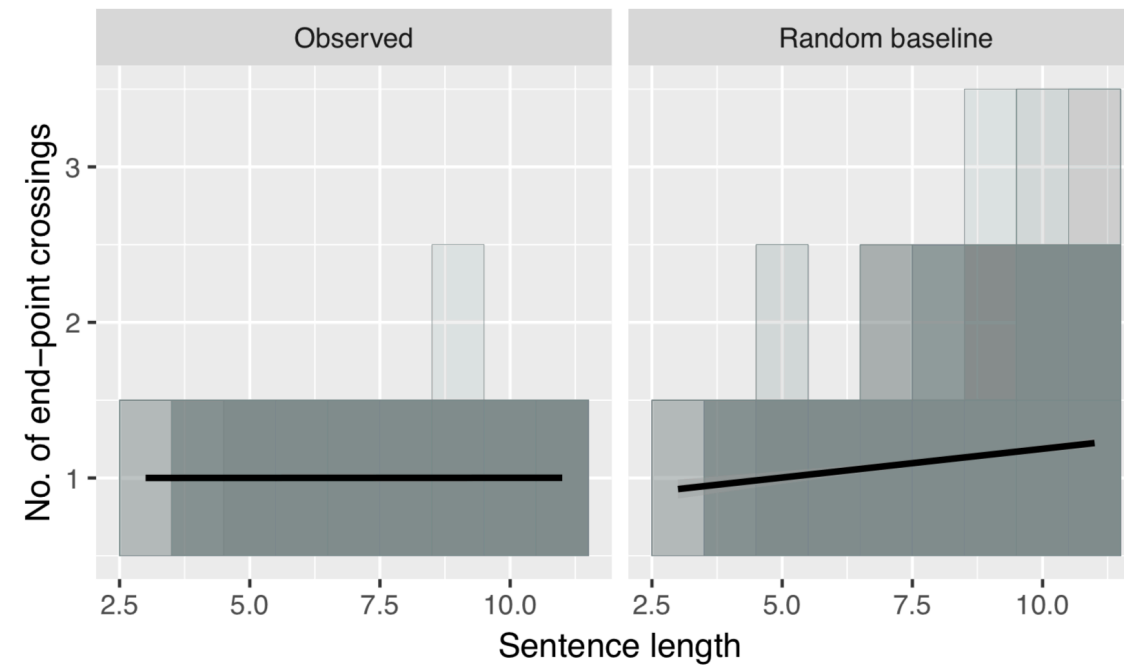


End-point Crossings

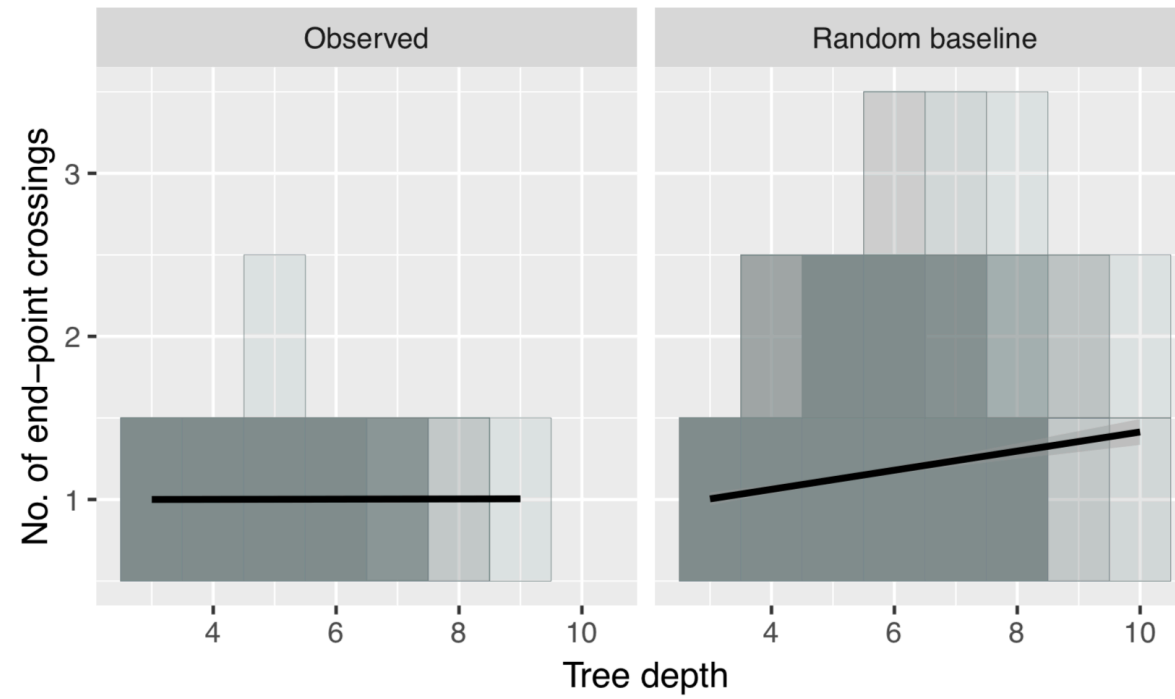


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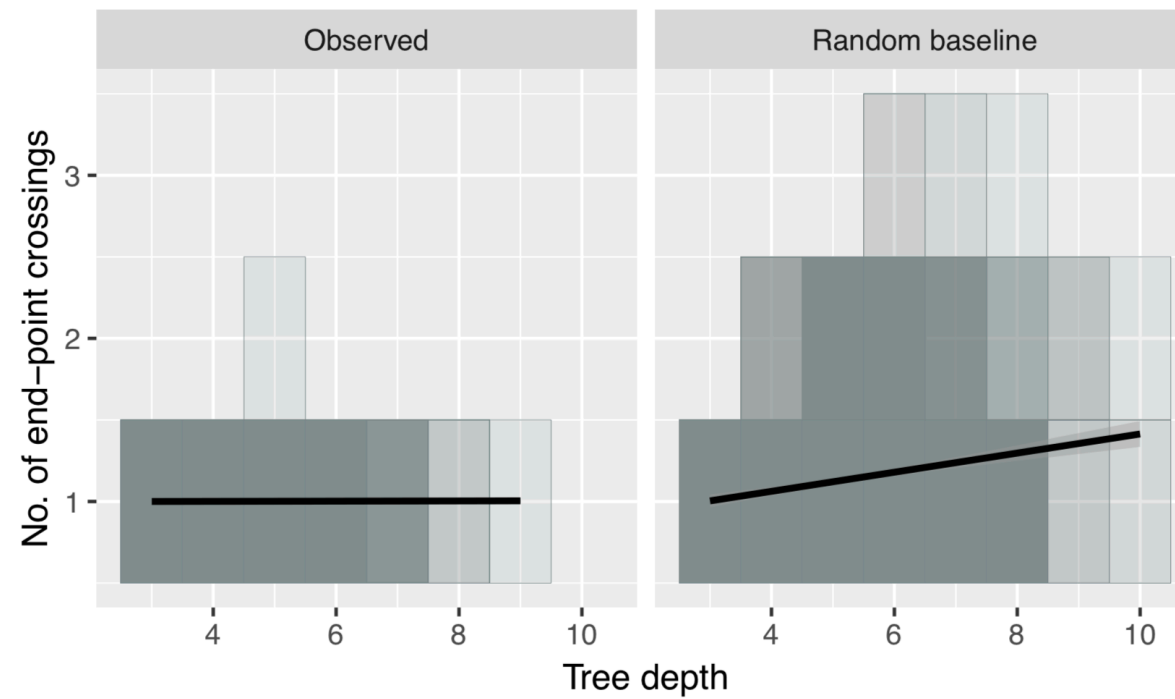
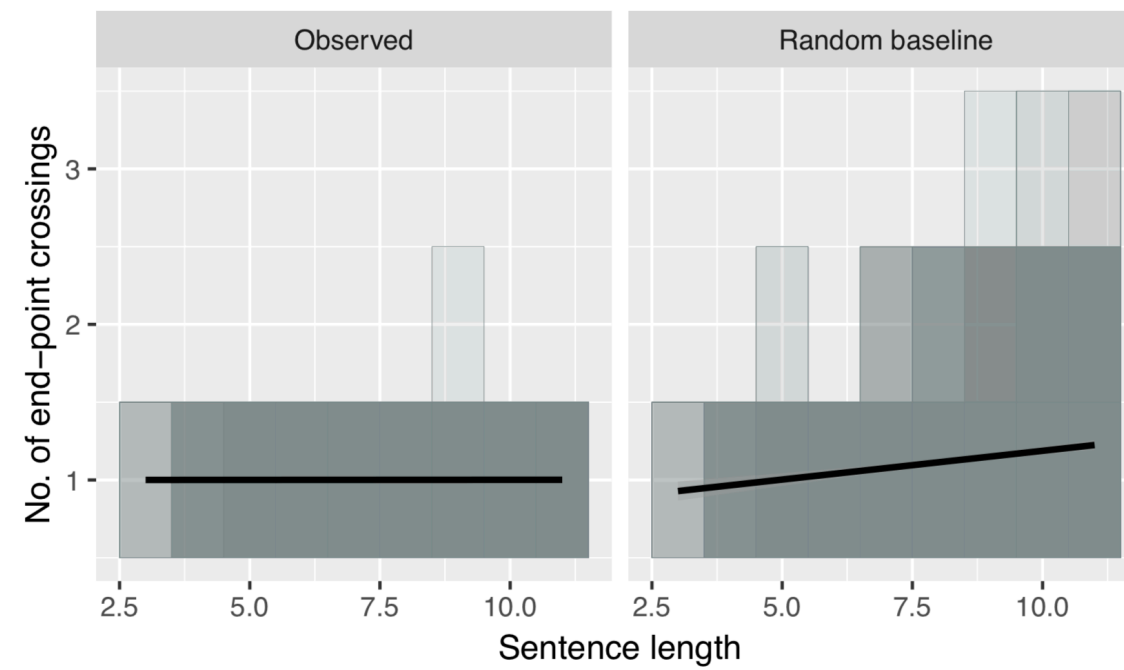
End-point Crossings



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End-point Crossings



Evidence for the True Constraint Hypothesis?

as a function of...	Gap degree	Edge Degree	End-point Crossings	Heads' Depth Difference
~ length				
~ arity				
~ depth				

 = significant interaction coefficient

 = nonsignificant interaction coefficient

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- Most crossing constraints differ between real and random trees **as a function of tree depth**.
 - Future work: Control for tree depth, arity, etc. in the random trees.

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- Future work can control for other factors:
 - Tree depth and arity
 - Dependency length
 - Could controlling crossing constraints explain the rarity of crossings?

Thanks all!

- All code is available online at https://github.com/yadavhimanshu059/measures_of_nonProjectivity
- Thanks to **Roger Levy** and **Tim O'Donnell** for discussion, and to our **SyntaxFest reviewers** for helpful suggestions.
- Thanks to the **TLT organizers!**