Modeling island effects with probabilistic tier-based strictly local grammars over trees

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Gradience and Syntactic Formalisms

How does one account for gradience in grammatical acceptability judgments?

Two possibilities:

1. It's not in syntax, so don't worry
2. Extend formalisms to allow for non-discrete judgments

This work

We investigate using the second strategy with new formalisms from subregular linguistics.

Collaborators

This is joint work across two institutions: UCI and Stony Brook

Charlie Torres

Kenneth Hanson

Thomas Graf

Connor Mayer

Outline

Strictly local languages

SL-k languages are generated by grammars that **prohibit certain substrings of length** k.

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Tier:	$\rtimes$	$\acute{\sigma}$		$\acute{\sigma}$	$\ltimes$
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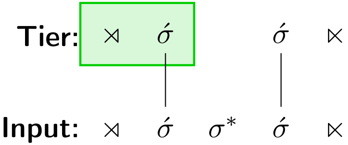

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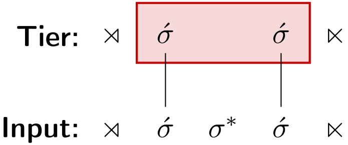

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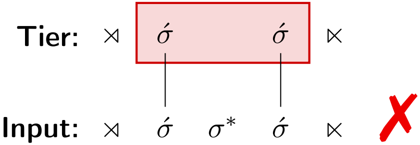

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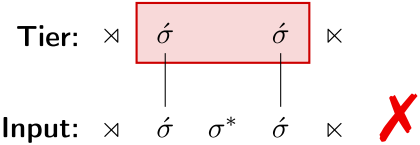

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Sometimes we want to model gradient properties

- Acceptability ratings
  (Albright and Hayes 2003; Daland et al. 2011)
- Production frequencies
  (Hayes and Londe 2006; Zuraw and Hayes 2017)

Example: Uyghur backness harmony (simplified)

Description: Vowels in a word must agree in backness

- The vowel /i/ is transparent (relevant later).

TSL grammar

$G = \{$ɑæ, æɑ, uy, ...$\}$

$T = \{$æ, ɑ, ø, o, y, u$\}$

Data

pæn-lær	'science-PL'
*pæn-lɑr	
ɑt-lɑr	'horse-PL'
*ɑt-lær	

Gradient blockers

Uvulars are **gradient blockers** in Uyghur wug tests (Mayer 2021)

Production rates with no uvular:

- pæt-lær (100%) vs. pæt-lɑr (0%)

Production rates with uvular:

- pæq-lær (75%) vs. pæq-lɑr (25%)

Increases tendency for back suffixes, but not categorically!

Does /q/ project?

String: $\rtimes$ p æ q l ɑ r $\ltimes$

Does /q/ project?

Projection 1:	⋊		æ			ɑ		⋉
String:	⋊	p	æ	q	l	ɑ	r	⋉

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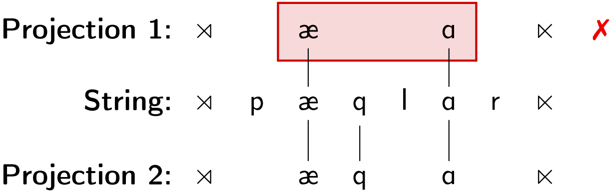

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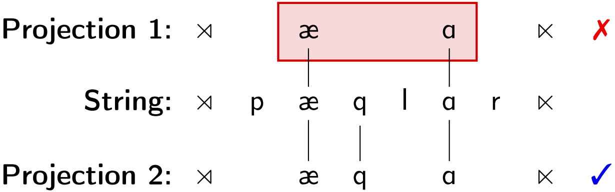

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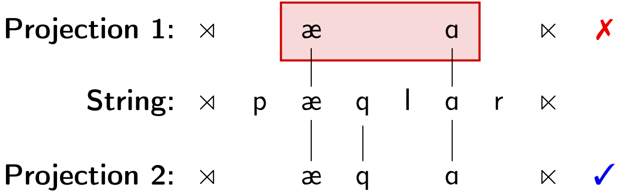

In either case, predicts categorical blocking or failure to block.

Probabilistic TSL

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Score: Sum of the probabilities of all *grammatical* projections.

A simple case

String: ⋊ p æ q l ɑ r ⋉

P_{proj}(harmonizing vowels) $= 1$
P_{proj}(q) $= 0.25$
P_{proj}(everything else) $= 0$

A simple case

Projection 1:	$\rtimes$		æ			ɑ		$\ltimes$
			|			|		
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Score for /pæqlɑr/: 0.25

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⋊ p æ q i q l ɑ r ⋉

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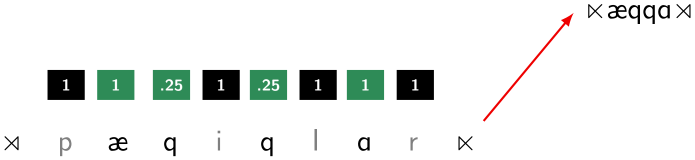

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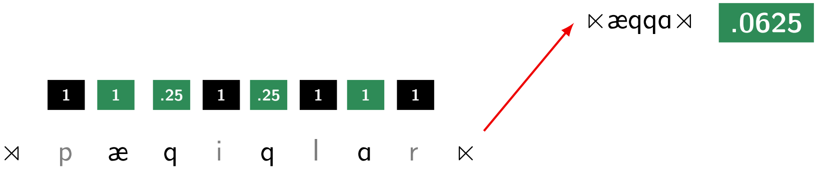

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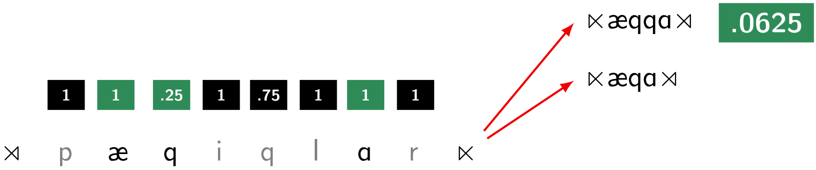

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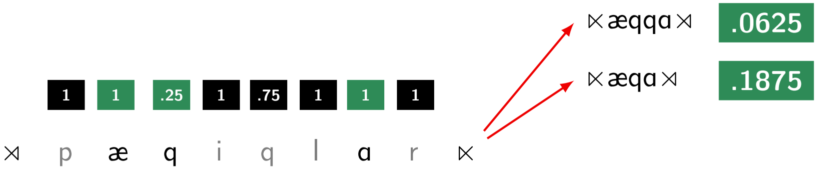

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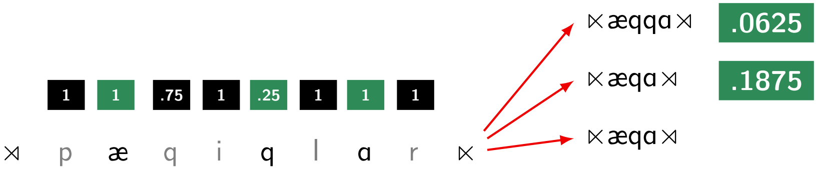

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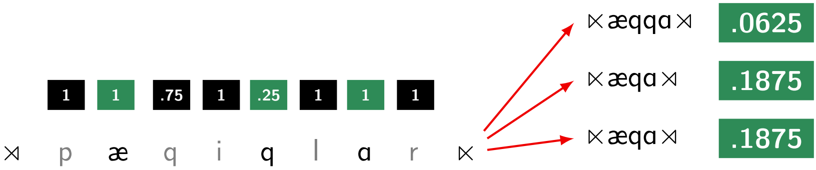

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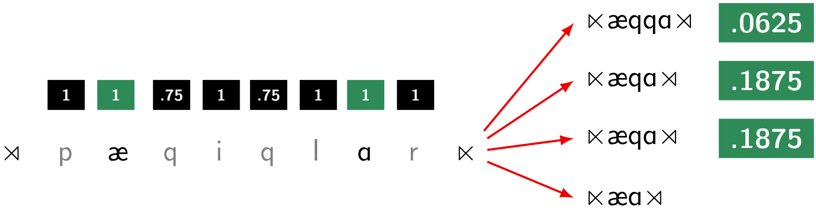

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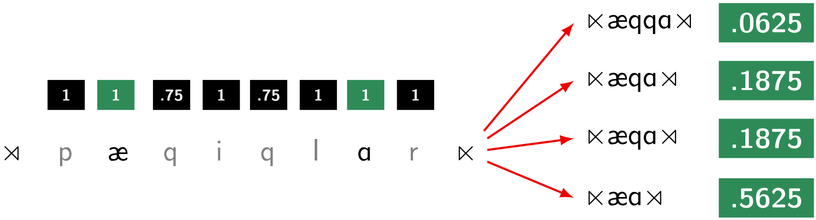

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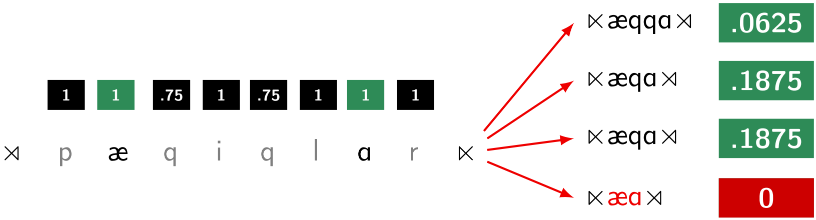

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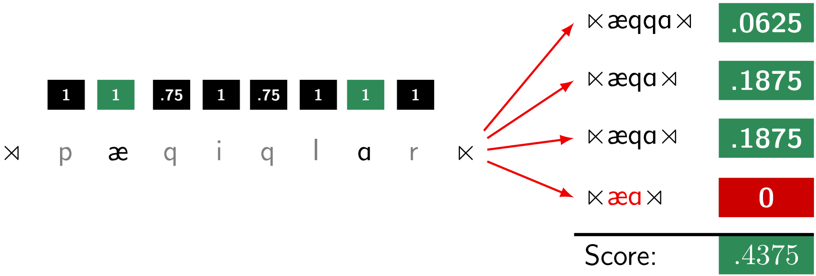

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2. Second, we will see if this can be extended in the same way to handle gradient syntactic judgments.

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Who does Mary think might buy what?

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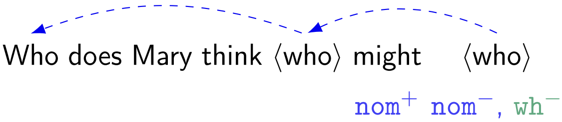

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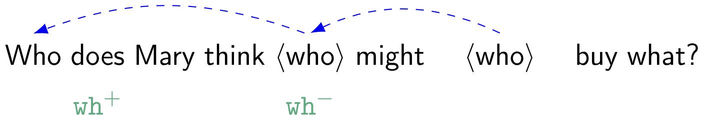

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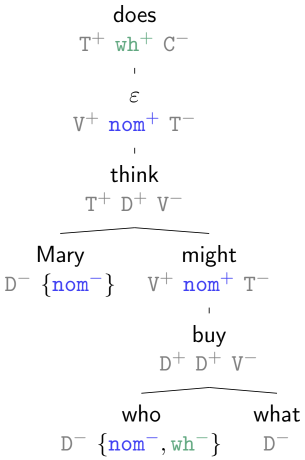
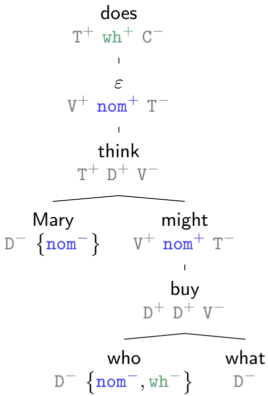


Movement in MGs is tier-based strictly local (TSL)



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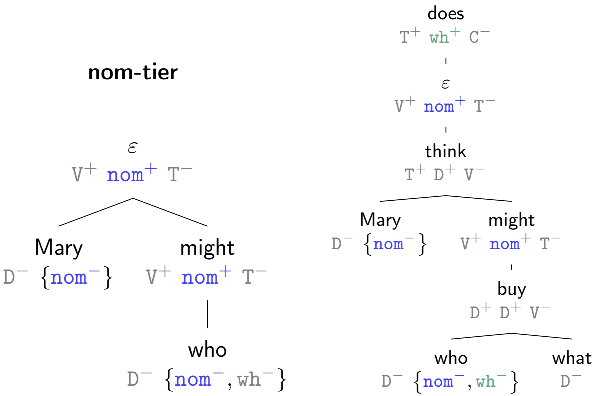

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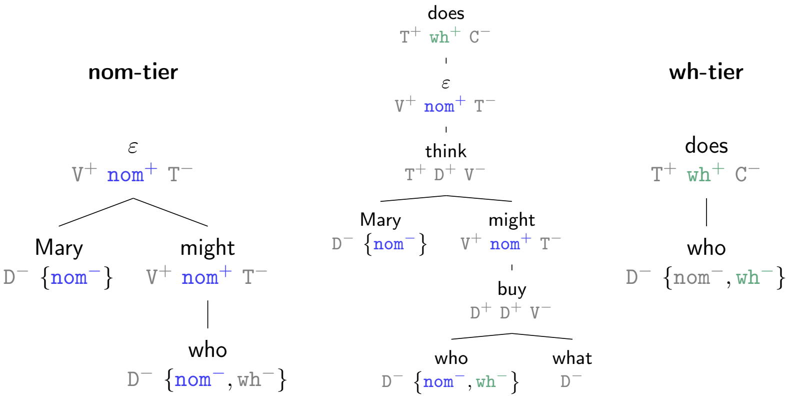

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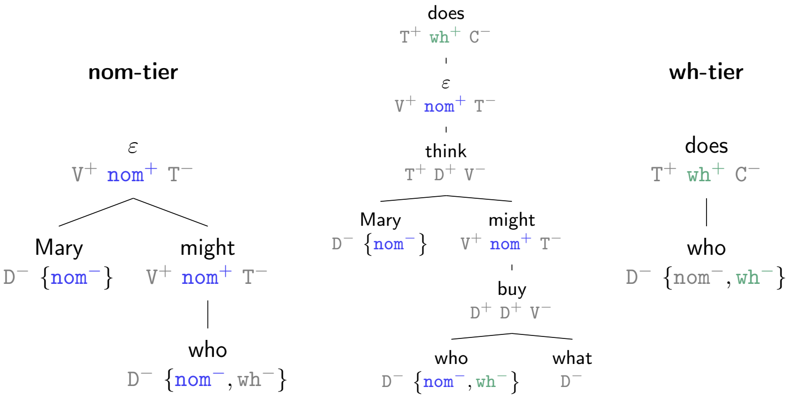
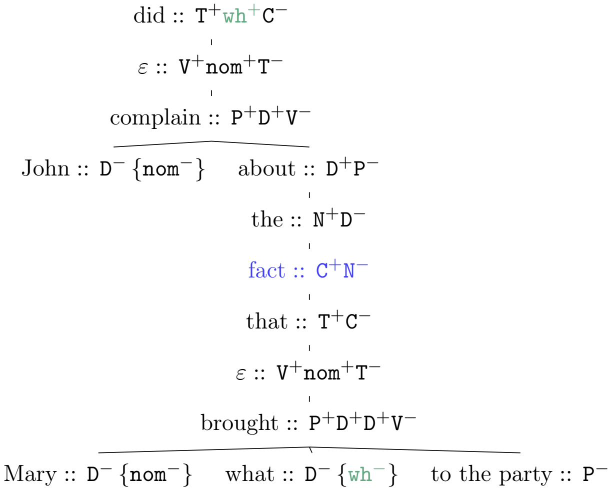


Feature checking as a constraint on each f-tier

1. Every $\texttt{f}^+$ has **exactly 1 $\texttt{f}^-$** among its daughters.
2. Every $\texttt{f}^-$ has **$\texttt{f}^+$ as its mother**.

Islands as tier blockers

(1) * What did John complain about the fact that Mary brought ⟨what⟩ to the party?



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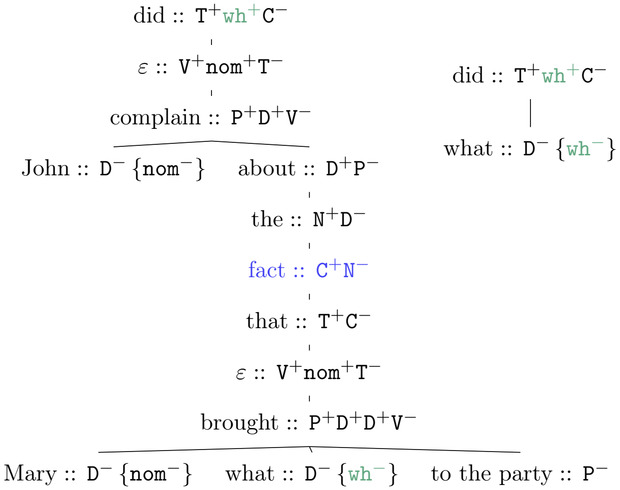

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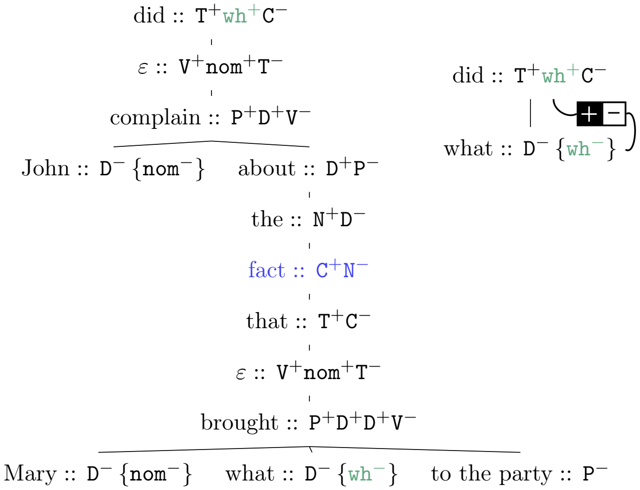

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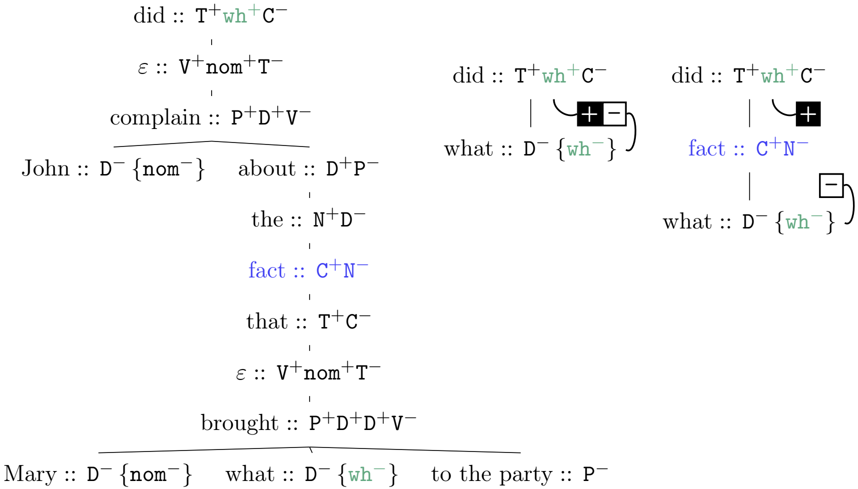
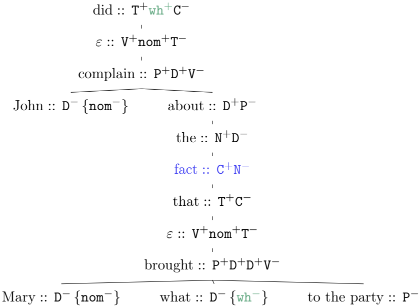


Probabilistic tree projection

- $P_{proj}(\text{fact}) = 0.7$
- $P_{proj} = 1$ for all `wh` nodes, 0 otherwise



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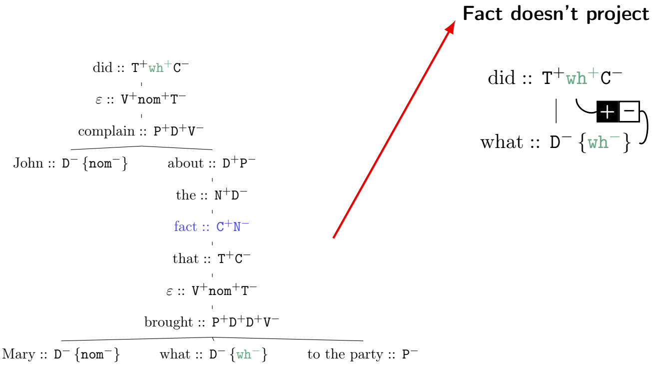

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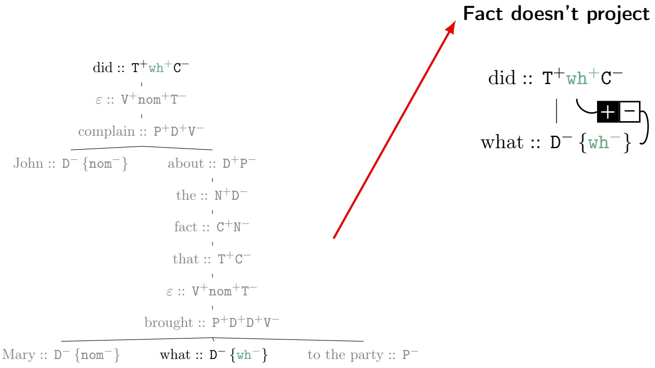

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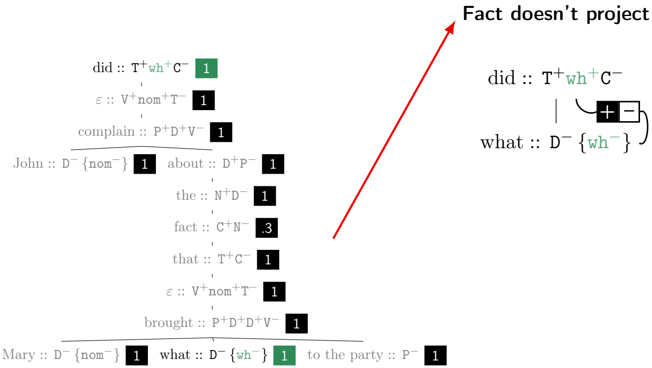

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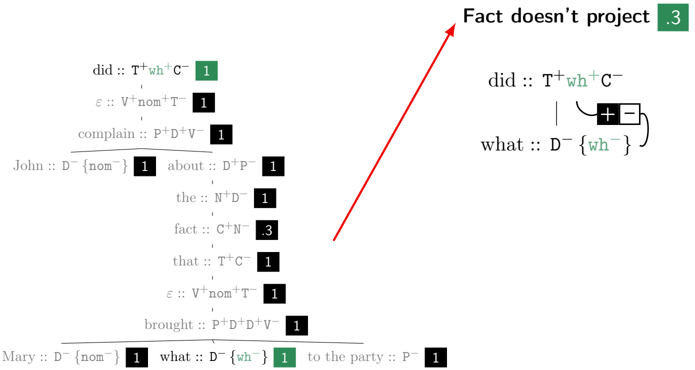

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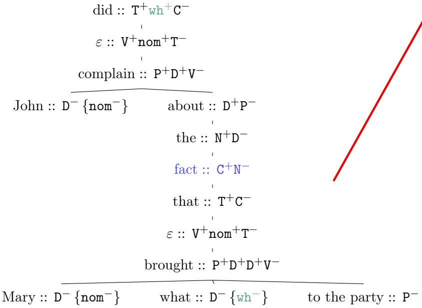

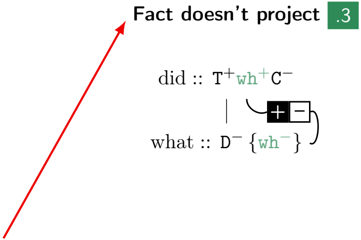

Probabilistic tree projection

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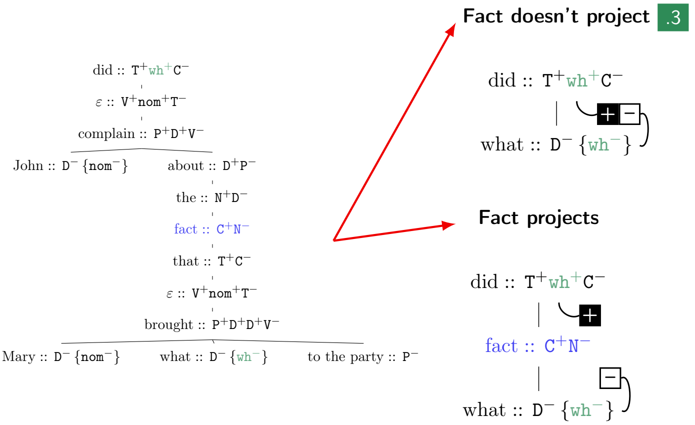

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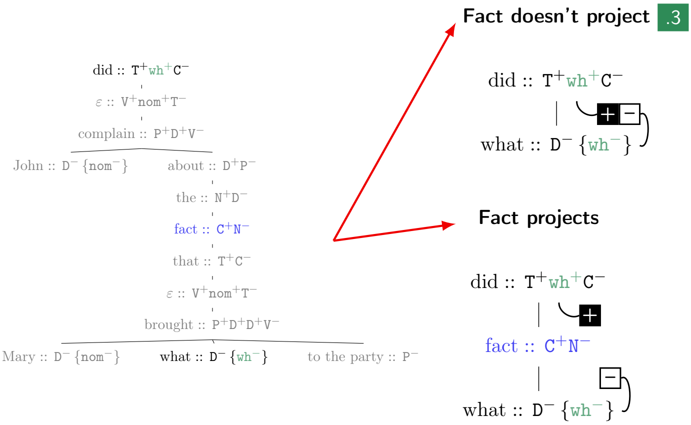

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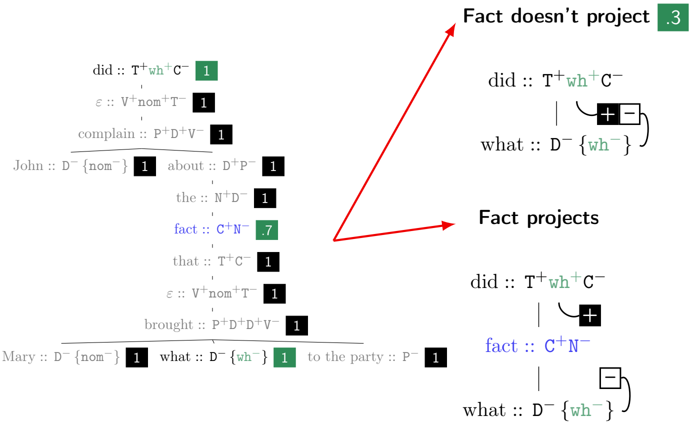

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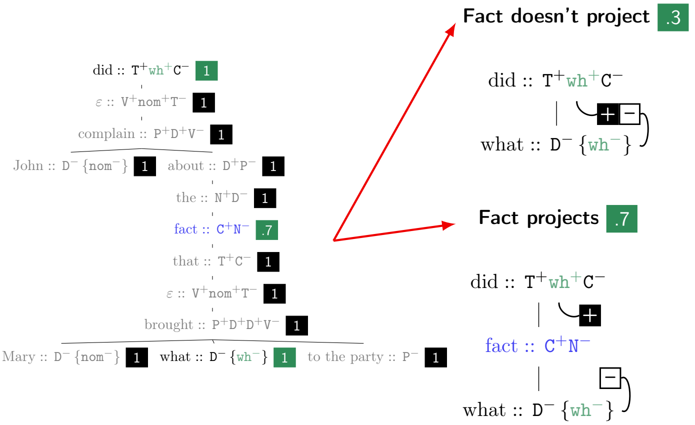

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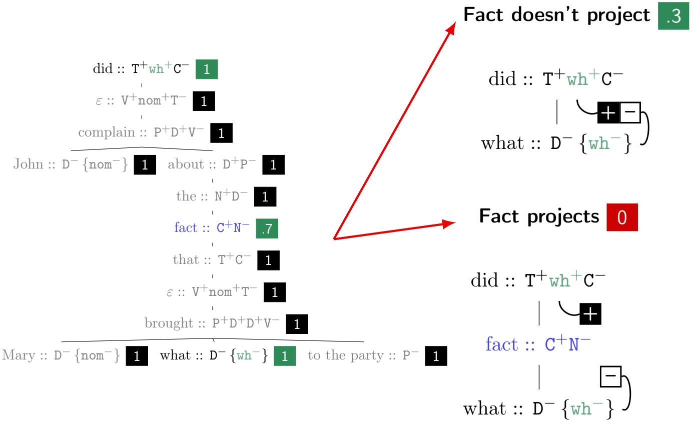

Modeling Island Effects using pTSL over Trees

Remainder of this talk: a modeling study that captures gradient island effects in experimental acceptability judgments.

Fit P_{proj} to English experimental data from Sprouse et al. (2016).

Figure: Jon Sprouse

The Sprouse data

The Sprouse data are sentences balanced for two factors:

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- Matrix or embedded clause extraction.

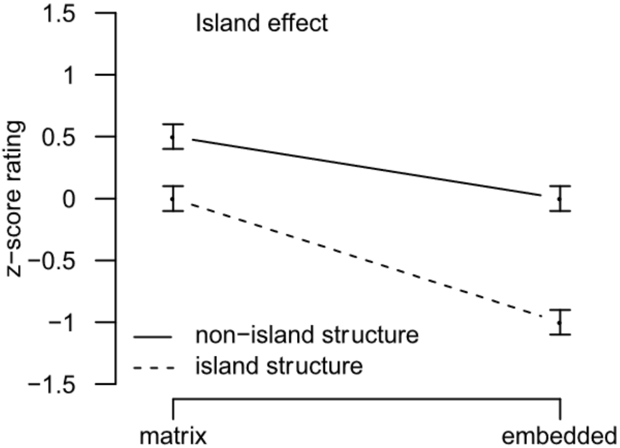
Example:

(2)
a. Who t thinks [that John bought a car]? (non-island, matrix clause)
b. What do you think [that John bought t]? (non-island, embedded clause)
c. Who t wonders [whether John bought a car]? (island, matrix clause)
d. What do you wonder [whether John bought t]? (island, embedded)

The Sprouse data

Only sentences with extraction from an embedded clause over an island structure should be ungrammatical.

- **Superadditivity**: effect of these two factors together is greater than their individual effects.



Island types

We restricted ourselves to three subsets of island effects:

1. **Whether islands**: *What do you wonder whether John bought t?
2. **Complex NP islands**: *Who did Mary deny the rumor that John likes t?
3. **Adjunct islands**: *Who did Mary complain because John likes t?

The Complex NP Constraint and Adjunct Island Constraint also apply to extraction out of relative clauses.

- We treat both as involving `wh` features for simplicity.

Adapting the data

Each of these sentences has a Likert score assigned by the participants.

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We converted each sentence in the data set into dependency tree format.

Fitting the model

Some projection probabilities set *a priori*:

- Most nodes set to 0
- `wh` nodes set to 1

Free parameters: Blockers in the discrete analysis.

- $\text{that} :: \texttt{T}^{+}\texttt{C}^{-}$ (*whether/adjunct islands*)
- $\text{whether} :: \texttt{T}^{+}\texttt{C}^{-}$ (*whether/adjunct islands*)
- $\text{if} :: \texttt{T}^{+}\texttt{C}^{-}$ (*whether/adjunct islands*)
- all nodes whose feature annotation contains the substring $\texttt{C}^{+}\texttt{N}^{-}$ (*complex NP islands*)

Fitting the model

Free parameters fit to data set consisting of dependency trees with mean normalized Likert ratings.

Model assigns values in [0,1] to each tree.

We find projection probabilities that minimize the mean squared error between model and human scores.

Super-additivity: Humans vs. pTSL

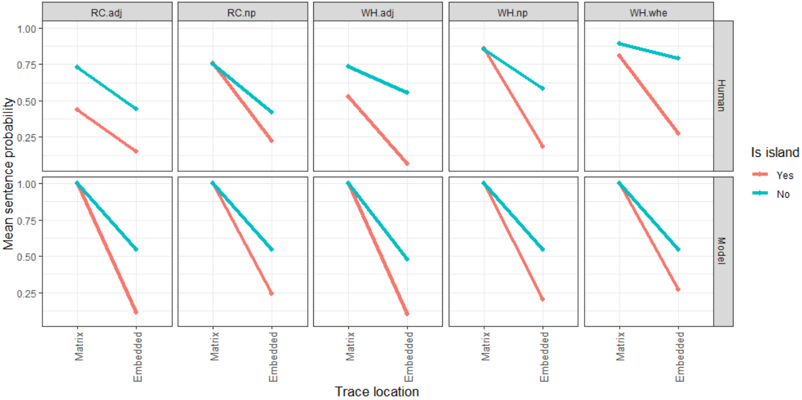

Figure: Super-additivity in a pTSL model

Fit Projection Probabilities

Node	Projection probability
that :: $\texttt{T}^{+}\texttt{C}^{-}$	.46
$\texttt{C}^{+}$ $\texttt{N}^{-}$	.63
whether :: $\texttt{T}^{+}\texttt{C}^{-}$	.73
if :: $\texttt{T}^{+}\texttt{C}^{-}$	.89

Table: Fit projection probabilities

Higher probability means greater propensity to block and induce island effects.

Discussion

The model succeeds in some respects:

- Captures supperadditivity
- Relative badness of different types of islands.

The model fails in other respects:

- Overpredicts superadditivity in some cases
- Doesn't account for variability in non-island cases.

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Some of the probabilities likely encode non-syntactic features:

- ‘that’ isn’t typically considered a blocker.
- Encodes (non-syntactic?) decrease in acceptability between matrix and embedded extraction.

Takeaways

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- pTSL over trees can capture superadditivity and gradience in syntactic island effects.

Take-home message

pTSL over trees lets us model gradience arising from grammatical factors.

Acknowledgments

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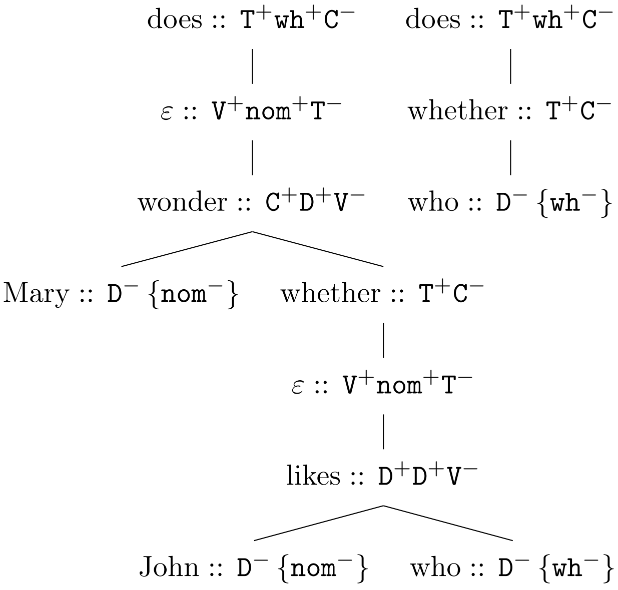
whether island



Adjunct island