Discontinuous Constituency and BERT: Case Studies of Dutch a.k.a. Diamonds are Forever

Gijs Wijnholds (+collaborators)

CLASP Seminar Göteborgs Universitet 17 February 2023

Project

Context:





Website: https://compositioncalculus.sites.uu.n



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Nichael Moortgat



Giuseppe Greco Postdoc









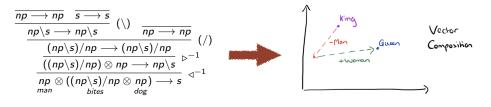


Adriana Correia* PhD

A bit of background

I want to integrate of the mathematical structures one finds in logic and linguistics, with state-of-the-art machine learning techniques in Natural Language Processing (NLP). The goal is to learn how to characterise natural language structures in a machine-learnable way, grounded in linguistic theory, with explainability at the forefront.

Compositional Distributional Semantics Coecke et al. [2010] Using category theory to unify grammar and meaning



Sentence structure as a proof

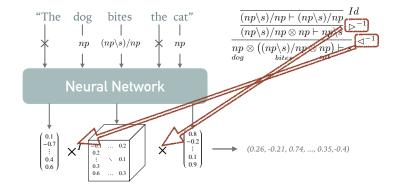
Word meaning as a tensor

Timeline

2008-2014: BSc AI, Utrecht University, MSc in Logic, ILLC, University of Amsterdam Proof Theory, Formal Grammar, Category Theory

A bit of background

A shift to the applied



Timeline

2016-2019: PhD in CS in the Theory Group, Queen Mary University of London, with prof. dr. Mehrnoosh Sadrzadeh Compositional Distributional Semantics, Machine Learning, Evaluation methods

THE ROBOTS ARE COMING



ChatGPT on a computer screen - Credit: rokas91 / DepositPhotos - License: DepositPhotos

TECH INNOVATION AI CHATGPT PLAGIARISM EDUCATION » MORE TAGS MONDAY, 16 JANUARY 2023 - 09:09

Dutch Students using ChatGPT to finish homework; Teachers aren't noticing

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NEWS | 18 January 2023

SHA

ChatGPT listed as author on research papers: many scientists disapprove

At least four articles credit the AI tool as a co-author, as publishers scramble to regulate its use.

Large-scale language models like GPT-3, BERT and others have attracted much attention in the NLP research community and beyond. But much is unknown about the mechanisms by which these models learn about and understand language, if at all.

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LMs use masked language modelling to learn to complete text:

The [MASK] is rising and all life on [MASK] will be [MASK] soon

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Stochastic Parrots "Contrary to how it may seem when we observe its output, an LM is a system for haphazardly stitching together sequences of linguistic forms it has observed in its vast training data, according to probabilistic information about how they combine, but without any reference to meaning: a stochastic parrot"

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A Central Question to Ask

▶ Do language models have any linguistic 'understanding'?

Motivation: discontinuities

Probing

- Extracting information from a language model by attaching a small task-specific neural network.
- ► Has been shown to reveal some syntactic understanding Rogers et al. [2020], Hewitt and Manning [2019]
- ► A latent bias persists because of focus on English and resources being context free/grammatically simple.

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w syntax in NLP

Discontinuity in Dutch

 $\begin{array}{c} \underset{xyzu_1u_2}{\text{Discontinuous patterns}}{\overset{(A_1)}{\text{results}}} \underset{results'about linguistic 'understanding' may not transfer between "anguages: $$ NP(x) TV(y) NP(z) NP(u) CV(v) VC(w_1, w_2)$} \begin{array}{c} \underset{(A_2)}{\overset{(A_3)}{\text{results}}} \underset{(A_2)}{\overset{(A_3)}{\text{results}}} \underset{(A_2)}{\overset{(A_3)}{\text{results}}} \underset{(A_3)}{\overset{(A_3)}{\text{results}}} \underset{(A_3)}{\overset{(A_3)$

- $\begin{array}{rcl} \operatorname{VC}(x,y) & \longleftarrow & \operatorname{TE}(x) \operatorname{INF}_{iv}(y) \\ \operatorname{VC}(zx,y) & \longleftarrow & \operatorname{TE}(x) \operatorname{INF}_{tv}(y) \operatorname{NP}(z) \end{array}$
- $VC(xy, zu_0u_1) \leftarrow NR(ar) Tab(y) Martin (a) Kinktenen(1) ziet leren fietsen$
- $VC(xyu, zv_1v_2) \leftarrow Nt(at) the (y) Marie (t) each (hd) enc (see, up) ach cycle$

 - Can a language model draw the links?

(a) 2-MCFG for control verbs.

 $S(xy_1y_2) \longleftarrow PREF(x) SUB(y_1, y_2)$ (*c*) de student die de door (*d*) de student beloof

Se

Ex

bel

vra

promis

Sentence examples

(a)

(b)

(EN)

[de student]

de student

the student

 $(a)_{A_1}$ de docent ziet [de student] [de h

(EN) the teacher sees

(b)

[de student] [vraagt] [

(a) de student belooft

de student vraagt

 (A_4)

 (A_5)

 (A_6)

 $(A_1^m)^{(a)}$

1

Understanding verb clusters

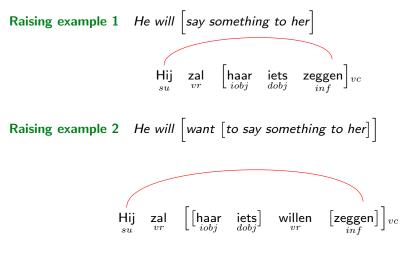
A Case Study (or two): Dutch verb clusters

Verb clusters arise in Dutch embedded clauses, when verb raisers are stacked, passing their subject/object to the embedded infinitive.



A Case Study (or two): Dutch verb clusters

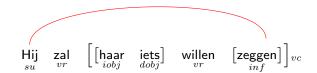
Verb clusters arise in Dutch embedded clauses, when verb raisers are stacked, passing their subject/object to the embedded infinitive.



zullen, willen: obligatory verb raiser

A Case Study (or two): subject flipping

Raising example 2 He will [want [to say something to her]]

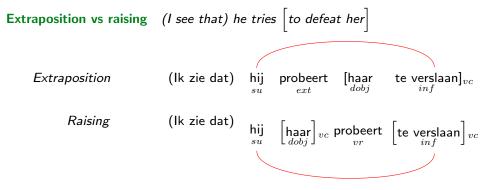


Raising example 3 He will want [to let her [say something]]

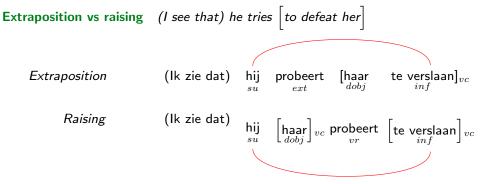


- zullen, willen: obligatory verb raiser
- laten: obligatory verb raiser, subject flipper

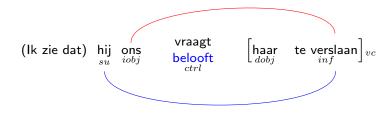
A Case Study (or two): raising versus extraposition



A Case Study (or two): raising versus extraposition



Control verbs (I see that) he asks/promises us to defeat her



A Case Study (or two): classifying verbal categories

Raising, Extraposition, Infinitives

Description	Examples
intransitive infinitive	vertrekken, stemmen, verliezen,
transitive infinitive with inanimate object	zeggen, begrijpen, merken,
transitive infinitive, animate object	ontmoeten, bedanken, kennen,
obligatory verb raiser	willen, zullen, moeten,
obligatory verb raiser, subject flipper	laten, doen
non-obligatory verb raiser	proberen, weigeren, trachten,
extraposition	proberen, weigeren, trachten,
extraposition, object control	verzoeken, dwingen, verplichten, .
extraposition, subject control	beloven, verzekeren, zweren,

Sources

Verbs sampled from Algemene Nederlandse Spraakkunst (ans.ruhosting.nl)

Probing pt. 1

Probing Discontinuity

Goal Setting up a general probing model that recognizes verb-subject dependencies, to evaluate whether Dutch language models contain lexical knowledge about control verbs, and whether they are invariant under word order permutations in the case of verb raising.

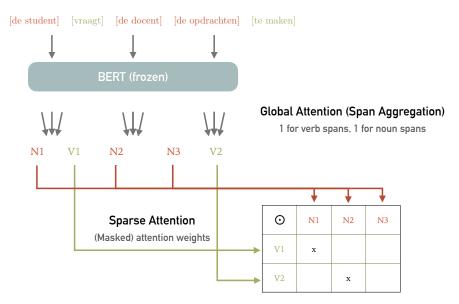
The setup

- 1. Design a probing model that can recognise verb-subject dependencies,
- 2. Gather appropriate training data,
- 3. Generate test data in a controlled/naturalistic way and test.

References

- Konstantinos Kogkalidis and Gijs Wijnholds. Discontinuous Constituency and BERT: A Case Study of Dutch. Findings of ACL 2022.
- DYI: https://github.com/gijswijnholds/discontinuous-probing

Probe design DESIGNING askste PROBEto the exercises

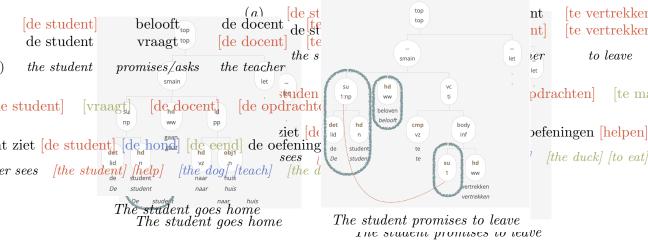


Sentences

Sentences

TRANING THE PROBE

Lassy-Small a gold standard dataset of written Dutch with ca. 65k sentences, both continuols an Sentence version version of the continuol standard dataset of written Dutch with ca. 65k sentences, both continuol s an Sentence version of the continuol standard dataset of written Dutch with ca. 65k sentences, both continuol s an Sentence version of the continuol sentence version o



The student promises to leave

(a)(b)

(c) de student die de docent belooft om de opdracht te maker

Probing attempt #1

Modelling discontinuities We use a *mildly context sensitive* grammar formalism, Multiple Context Free Grammar, to generate test samples.

Syntax vs. lexicon One grammar for verb raising constructions, a separate one for control verbs:

- (a) de docent ziet [de student] [de collega] [de professor] de oefeningen [helpen] [leren] [maken]
- (EN) the teacher sees [the student] [help] [the colleague] [teach] [the professor] [to do] the exercises

Validation vs test results While the prober performs very well, the test sets are challenging:

Model	Lassy	Control	Raising		
BERTje	97.6	48	43.1		
RobBERT	92.5	40.6	29.2		

A downside because the grammar is rule-based, we need to write complex specifications of how subjects are inherited by verbal complements.

	# Nouns				Tree Depth				Rule				
Model	2	3	4	5	2	3	4	A_1^X	A_2^X	A_3	A_4	A_5	A_6
												-	

Learn you a categorial grammar for great good!

A user-friendly format: Natural Deduction

Structures, sequents Judgements $\Gamma \vdash A$ with A a formula, Γ a structure:

$$\Gamma, \Delta$$
 ::= $A \mid \Gamma \cdot \Delta$

Axiom, logical rules For the base logic, we have the *axiom* $A \vdash A$ and as logical inference rules, for each connective an *elimination* rule and an *introduction* rule, e.g.

$$\frac{\Gamma \vdash A \quad \Delta \vdash A \backslash B}{\Gamma \cdot \Delta \vdash B} \backslash E \qquad \frac{A \cdot \Gamma \vdash B}{\Gamma \vdash A \backslash B} \backslash I$$

A user-friendly format: Natural Deduction

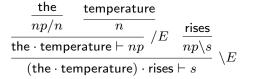
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Example in steno format



Notation: $\Gamma[\Delta]$ for a structure Γ containing a substructure Δ

Control operators

The need for control languages exhibit phenomena that seem to require a form of

reordering, restructuring, copying

The logical answer Structures $\Gamma, \Delta ::= A \mid \langle \Gamma \rangle \mid \Gamma \cdot \Delta$

$$\frac{\langle \Gamma \rangle \vdash A}{\Gamma \vdash \Box A} \Box I \qquad \qquad \frac{\Gamma \vdash \Box A}{\langle \Gamma \rangle \vdash A} \Box E$$
$$\frac{\Gamma \vdash A}{\langle \Gamma \rangle \vdash \Diamond A} \Diamond I \qquad \qquad \frac{\Delta \vdash \Diamond A \quad \Gamma[\langle A \rangle] \vdash B}{\Gamma[\Delta] \vdash B} \Diamond E$$

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$$\begin{array}{ccc} \frac{\langle \Gamma \rangle \vdash A}{\Gamma \vdash \Box A} \Box I & \qquad \frac{\Gamma \vdash \Box A}{\langle \Gamma \rangle \vdash A} \Box E \\ \\ \frac{\Gamma \vdash A}{\langle \Gamma \rangle \vdash \Diamond A} \diamondsuit I & \qquad \frac{\Delta \vdash \Diamond A \quad \Gamma[\langle A \rangle] \vdash B}{\Gamma[\Delta] \vdash B} \diamondsuit E \end{array}$$

Structure global rules $\rightsquigarrow \diamondsuit$ controlled restricted versions, e.g.

$$\begin{array}{rl} A^{\diamond}: & (A \bullet B) \bullet \Diamond C \longrightarrow A \bullet (B \bullet \Diamond C) \\ C^{\diamond}: & (A \bullet B) \bullet \Diamond C \longrightarrow (A \bullet \Diamond C) \bullet B \end{array}$$

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Multimodal generalization families $\{\Diamond_i, \Box_i\}_{i \in I}$ for particular structural choices

Encoding dependency structure

Heads vs dependents

Dependency roles articulate the linguistic material on the basis of two oppositions:

- head complement relations
 - ▶ verbal domain: subj, (in)direct object, ...
 - ▶ nominal domain: prepositional object, ...
- adjunct head relations
 - ▶ verbal domain: (time, manner, ...) adverbial
 - ▶ nominal domain: adjectival, numeral, determiner, ...

Compare: fa-structure: function vs argument

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Compare: fa-structure: function vs argument

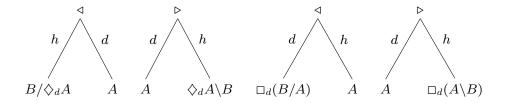
Orthogonality The fa and the dependency articulation are in general not aligned. This asks for a multidimensional type logic.

E.g. Determiner. Semantically, characteristic function of $(\llbracket N \rrbracket, \llbracket VP \rrbracket)$ relation; morphologically, dependent on head noun.

Defining a headed product

Multimodal generalization families $\{\diamondsuit_d, \Box_d\}_{d \in DepLabel}$

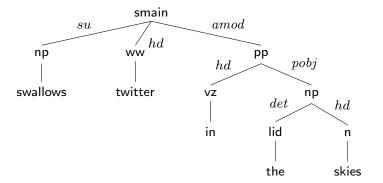
- \blacktriangleright $\Diamond_d A \backslash C$, $C / \diamondsuit_d B$ head functor assigning dependency role d to its complement
- ▶ $\square_d(A \setminus C)$, $\square_d(C/B)$ dependent functor projecting adjunct role d



Example Determiner: $\Box det(np/n)$, after projecting its determiner dependency role it can act as a function of its argument noun.

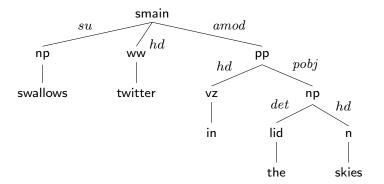
Extracting types from structured data

Dutch treebank LASSY Annotation DAGs, nodes: synt categories, edges: dependency relations. Re-entrancy: higher-order types.



Extracting types from structured data

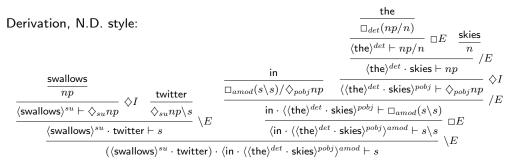
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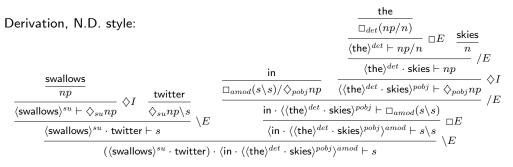
Extracted types:

swallows : np twitter : $\Diamond_{su}np \setminus s$ in : $\Box_{amod}(s \setminus s) / \Diamond_{pobj}np$ the : $\Box_{det}(np/n)$ skies : n

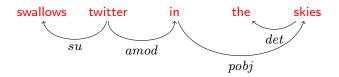
Dependency structure



Dependency structure



Induced dependency structure:



 \sim within dependency domain, outgoing arcs from head to (head of) dependents

Benefitting from a multidimensional setup

Kokos Kogkalidis worked on resources and neural tools for parsing Dutch in the multimodal setup:

- Kogkalidis et al 2020a, Æthel: Automatically extracted typelogical derivations for Dutch. LREC.
- ▶ Kogkalidis et al 2020b, Neural proof nets. CoNLL
- ► Kogkalidis et al 2022, Geometry-Aware Supertagging with Heterogeneous Dynamic Convolutions, arXiv

If you want to try things out, see the readme on

https://github.com/konstantinosKokos/lassy-tlg-extraction

for the extracted proofbank

https://github.com/konstantinosKokos/dynamic-proof-nets

for the parser

Parser explained in one slide

Proof net



Goal

 $np_1 \quad \mathbf{X}$

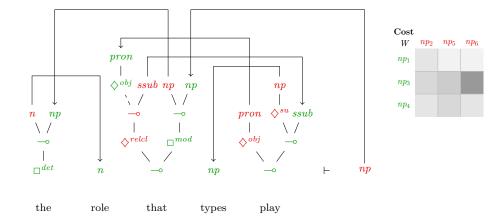
 np_3

 np_4

 np_2 np_5 np_6

х

X



 $\stackrel{\eta}{\leadsto} \mathbf{\nabla}^{mod}(\mathsf{that} \ \Delta^{relcl} \lambda \mathbf{x}.(\mathsf{play} \ \mathbf{x} \ \Delta^{su} \ \mathsf{types})) \ (\mathbf{\nabla}^{det} \mathsf{the role})$

Probing pt. 2

Handling verb clusters: the ACG approach

▶ the Abstract Categorial Grammar method

abstract syntax, divergent compositional translations:

 $[\cdot]^{string}$ string semantics

 $[\cdot]^{sem}$ meaning assembly

The ACG method is easily adapted to our NL source: words as abstract constants.

Simple combinatorics, inflated type homomorphism String semantics: higher-order modelling of tuples

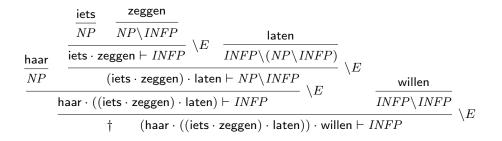
$$[INFP] = (\sigma \multimap \sigma \multimap \sigma) \multimap \sigma \qquad \triangleq \sigma^{(2)}$$

References

- Michael Moortgat, Konstantinos Kogkalidis and Gijs Wijnholds. Diamonds are Forever: Theoretical and Empirical Support for a Dependency-Enhanced Type Logic. To appear in: Logic and Algorithms in Computational Linguistics 2021.
- DYI: https://github.com/gijswijnholds/malin_2022

ACG method (cont'd)

Abstract syntax The syntax types don't yield the surface string, but the closest you can get using logical rules only.



ACG method (cont'd)

Abstract syntax The syntax types don't yield the surface string, but the closest you can get using logical rules only.

$$\frac{\underset{NP}{\text{haar}}}{\underset{NP}{\underline{NP}}} \quad \frac{\underset{NP}{\underbrace{iets}} \quad \frac{zeggen}{\underline{NP} \setminus INFP}}{(\text{iets} \cdot zeggen \vdash INFP} \setminus E \quad \frac{\underline{laten}}{INFP \setminus (NP \setminus INFP)} \setminus E \\ \frac{\underbrace{haar}{(\text{iets} \cdot zeggen) \cdot |aten \vdash NP \setminus INFP}}{\underbrace{haar}{((\text{iets} \cdot zeggen) \cdot |aten) \vdash INFP} \setminus E \quad \frac{\underline{willen}}{INFP \setminus INFP} \\ \frac{f \quad (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot \text{willen} \vdash INFP} \\ (\text{iets} \cdot zeggen) \cdot |aten) \mapsto InfP \quad \forall INFP \\ \frac{f \quad (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP} \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeggen) \cdot |aten)) \cdot willen \vdash INFP \\ (haar \cdot ((\text{iets} \cdot zeg$$

$$\begin{split} &[\operatorname{zeggen}]^{string} &= \lambda x \lambda f.(f \ x \ \operatorname{zeggen}) &:: \ \sigma \multimap \sigma^{(2)} \\ &[\operatorname{willen}]^{string} &= \lambda q \lambda f.(q \ \lambda y \lambda z.(f \ y \ \operatorname{willen} \cdot z)) &:: \ \sigma^{(2)} \multimap \sigma^{(2)} \\ &[\operatorname{laten}]^{string} &= \lambda q \lambda x \lambda f.(q \ \lambda z \lambda w.(f \ x \cdot z \ \operatorname{laten} \cdot w)) &:: \ \sigma^{(2)} \multimap \sigma \multimap \sigma^{(2)} \end{split}$$

 $[\dagger]^{string} = \lambda f.(f \text{ haar} \cdot \text{iets willen} \cdot \text{laten} \cdot \text{zeggen})$ compare $[\dagger]^{sem} = \text{WANT} (\text{LET} (\text{SAY SOMETHING}) \text{ HER})$

Dependency enhancement

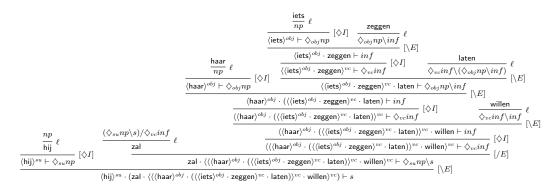
function types $A \backslash B \rightsquigarrow \diamondsuit_d A \backslash B$

vc: verbal complement

$$\frac{\frac{\mathsf{iets}}{np}}{\frac{\langle \mathsf{iets} \rangle^{obj} \vdash \Diamond_{obj} np}{\langle \mathsf{iets} \rangle^{obj} \cdot \mathsf{zeggen} \vdash \mathsf{inf}} \setminus E}{\frac{\mathsf{haar}}{np}} \Diamond I \quad \frac{\langle \mathsf{iets} \rangle^{obj} \cdot \mathsf{zeggen} \vdash \mathsf{inf}}{\langle \langle \mathsf{iets} \rangle^{obj} \cdot \mathsf{zeggen} \rangle^{vc} \vdash \Diamond_{vc} \mathsf{inf}} \Diamond I \quad \frac{\mathsf{laten}}{\Diamond_{vc} \mathsf{inf} \setminus (\Diamond_{obj} np \setminus \mathsf{inf})} \setminus E}{\langle \langle \mathsf{iets} \rangle^{obj} \cdot \mathsf{zeggen} \rangle^{vc} \vdash \Diamond_{vc} \mathsf{inf}} \land I \quad \frac{\mathsf{laten}}{\langle \mathsf{vecinf} \setminus (\Diamond_{obj} np \setminus \mathsf{inf})} \setminus E}{\langle \langle \mathsf{iets} \rangle^{obj} \cdot \mathsf{zeggen} \rangle^{vc} \cdot \mathsf{laten} \vdash \Diamond_{obj} np \setminus \mathsf{inf}} } \langle E \quad \frac{\langle \mathsf{haar} \rangle^{obj} \cdot (\langle \langle \mathsf{iets} \rangle^{obj} \cdot \mathsf{zeggen} \rangle^{vc} \cdot \mathsf{laten}) \vdash \mathsf{inf}}{\langle \langle \mathsf{haar} \rangle^{obj} \cdot (\langle \langle \mathsf{iets} \rangle^{obj} \cdot \mathsf{zeggen} \rangle^{vc} \cdot \mathsf{laten}) \rangle^{vc} \vdash \Diamond_{vc} \mathsf{inf}} } \langle E \quad \frac{\mathsf{willen}}{\langle \mathsf{vecinf} \setminus \mathsf{inf}} \langle E \quad \mathsf{vecinf} \rangle \langle E \rangle^{vc} \mathsf{inf} \wedge \mathsf{inf}} \langle \mathsf{vecinf} \rangle \langle E \rangle^{vc} \mathsf{inf} \mathsf{vecinf} \rangle \langle E \rangle^{vc} \mathsf{vecinf}} \langle \mathsf{vecinf} \rangle^{vc} \mathsf{vecinf} \rangle \langle E \rangle^{vc} \mathsf{vecinf} \rangle^{vc} \mathsf{vecinf}} \langle \mathsf{vecinf} \rangle^{vc} \mathsf{v$$

(WANT $\triangle^{vc}((\text{LET } \triangle^{vc}(\text{SAY } \triangle^{obj} \text{ SOMETHING})) \triangle^{obj} \text{ HER}))$

Recap: Doing it the Diamond Way



273 abstract samples Each word is a unique instance of a word category, used to generate many there samples

[Moortgat et al., 2022]

Populating the lexicon

The lexicon

Category	Description	Examples
INF0	intransitive infinitive	vertrekken, stemmen, verliezen,
INF1	transitive infinitive with inanimate object	zeggen, begrijpen, merken,
INF1A	transitive infinitive, animate object	ontmoeten, bedanken, kennen,
IVR0	obligatory verb raiser	willen, zullen, moeten,
IVR1	obligatory verb raiser, subject flipper	laten, doen
IVR2	non-obligatory verb raiser	proberen, weigeren, trachten,
INF2	extraposition	proberen, weigeren, trachten,
INF3	extraposition, object control	verzoeken, dwingen, verplichten,
INF4	extraposition, subject control	beloven, verzekeren, zweren,
OBJ1A	animate direct object	Karin, Wouter,
OBJ1I	inanimate direct object	iets, veel, een ding,
OBJ2	indirect object	Karin, Wouter,

Sources

- Verbs sampled from Algemene Nederlandse Spraakkunst (ans.ruhosting.nl)
- ▶ Names samples from the Nederlandse Voornamenbank (www.meertens.knaw.nl/nvb)

which allows us to better tune and adjust the focus of our quantitative analysis. In Appendix 4 we provide a listing of all verbal categories used through the generation, **Results (1/3)** ogether with a short description and a few example lexical items; the list might prove useful in following along with our analysis in the next few sections.

Validation vs test resultsThe probe again does not perform well on the generateddata:3.1 Number of Nouns

	Validation set (Lassy)	Test set (generated)
As a preliminary ste	p, we measure test set p	reformance in relation to the number $\frac{79.47}{100}$, which we imagine can
of subject candidates	in the sentence (i.e. nur	nber of notifies), which we imagine can
<u>confound the model's</u>	ability to make a correct	t semantic judgement, and present our
results in Table 2.	-	

Table 2 Accuracy results by number of nouns.

Number of nouns	2	3	4
Accuracy	86.87	75.66	68.76
Random Baseline	50.00	33.33	25.00

As expected, the accuracy does indeed show a correlation to the number of attractors. The correlation is, however, rather weak; accuracy is surprisingly low in comparison to the validation set even in the presence of a single attractor, and only moderately declines as they increase, remaining consistently high above the random baseline.

3.2 Verbal Type

Since the number of nouns is not that telling of a feature in distinguishing correct versus erroneous predictions, the next thing to group results by by is the type of

which allows us to better tune and adjust the focus of our quantitative analysis. In Appendix 4 we provide a listing of all verbal categories used through the generation, **Results** (1/3) together with a short description and a few example lexical items; the list might prove useful in following along with our analysis in the next few sections.

Validation vs testarcesus such the probe again does not perform well on the generated data:

3.1 Number of Nouns Table 1 Accuracy and baseline results on the validation (Lassy) and test set

Validation set (Lassy) Test set (generated) Validation set (Lassy) Test set (generated) As a preliminary step, we measure test set performance in relation to the number

results in Table 2.

By number of nouns Just a check that the results follow the expected pattern: which the wave wave better bunerable adjust the focus of our quantitative analysis. In

Appendix 4 we provide a listing of all verbal categories used through the generation, together with a short description and a few example lexical 4 tems; the list might prove useful in following along with our analysis in the next few sections.

Random Baseline 50.0	0 33.33	25.00
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3.1 Number of Nouns As expected, the accuracy does indeed show a correlation to the number of attractors. The correlation is, however, rather weak; accuracy is surprisingly low in As correlinioarto the watermeasure testash nerformence of a slatige anthropy make only of subject and idates is the server case, remating to a subject and intersection of su confound the model's ability to make a correct semantic judgement, and present our results in Table 2.

Tably 2 Averbay Type by number of nouns.

Number of nouns 4 2 3

Accine the number of nounsismot that tolling of a feature in distinguishing correct **P**₀, versus erroneous predictions othe next thing to group results by by is the type of

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Random Baseline	50.00	33.33	25.00
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3.1 Number of Nouns

By verbal type Extraposition easies when a concentration of the presence of a share of the presence of the pre

of subject candidates in the sentence (i.e. number of nouse), which we imagine san on

Verbal type	Raising	Extraposition	Infinitive present ou
Accuracy	81.00	87.03	68.77
Random	39.86	38.27	39.24
Table 2 Averagy	white by number of nou	ns.	

Number of nouns 2 3 4

Accine the number of nounses not that tolling of a feature in distinguishing correct **P**₀, versus erroneous predictions othe next thing to group results by by is the type of

governing raising constructions are harder to disentangle compared to their extraposing relatives, and infinitives are remarkably worse off than either. We provide a further specification of accuracy broken down by individual verb categories in Table 10, but note that these results do not show a striking difference between individual Results v(2 / 19 pries.

Dominance

3.3 Verb Domina	nce _{BJ2} (DBJ_1^I	IVR_0	IVR	1 IN	F ₁
hij zal	haar :	iets	willen	lat	en ze	ggen
To tell what exactly	it i beh at ma	skonviethi	nigives wandtfficu	ılt∕€otr	BERTsjæ	to understand,
we filter predictions						
and group them first			OBdse's govern	π E gv	₩ ,1and	afterwards by
the the difference of the the the					laten	zeggen
he will tr	У	her	something	to	let	say

Table 4 Accuracy results by dominance, distinguishing verb raisers and extraposition verbs.

Governed ver	Dominated verb, grouped by verbal type Dominating verb, by subcategory					
	Dominated by raising	Overall	IVR0	IVR1	IVR2 $\frac{\text{tive}}{10}$	9
_	Accuracy Random Baseline	76.18 39.86	78.54 41.06	71.41 37.09	77.95 41.05	_
	Dominated by extraposition	Overall	INF2	INF3	INF4	_
	c Accuracy — Random Baseline	66.70 38.27	86.74 42.58	57.12 35.13	47.12 30 35.13 <u></u>	_

- ▶ Accuracy declines for verbs governed by a subject flipping verb raiser (IVR1)
- Under an extraposition verb, control verbs (INF3/INF4) are the challenging ones.

induce linguistically complex cases, that are in turn challenging for the language model to analyze.

Results (3/34) Semantic Equivalence, Syntactic Variation

Semantic equiv	Aundatase	complay we	bsthat pressa may induce e	րվի inglug ither. Th	ffele e latter	Fler ASAramatisu Maseurealiza-
tion, but identi	they produ	ce drastically	differing abst	act synta	x trees	, that in turn get materialized
	as distinct semantic te	permutations hij zal had rms; see Exa he will her	of the same learning of the sa	xical iter ^{(2]} <i>te wil</i> ^{v.} to wa	ns. but <i>len ont</i> nt me	with identical meanings, i.e. moeten et
	(2) b .		<i>b great</i> blyEA jihg			
		he will ber	1 .	r to war		
10	b.		berevan trans	et her's id	AH@AH	and Author
		he will try	he	r to war	nt mee	et
Table	8 Accuracy re	sullactowialisting	to. wantptointoo	utohenr'ucti	ons, with	n identical semantic terms.
Results Extra	position_e	asier const	rucțion to l	nandle,	mino	r difference on the surround-
ing context.						owards either of the two con-
0						tical semantic terms (modulo
	the IV R2/f	NF2 distincti	on), differing	Context i	e word n the ser	Below of their respective sur-
						th Bplow ition of each inspected
	verb withir	the AST (that	at being the an	biguous	yerb its	elf ₈₀₁₅ a verb occurring above
		in the tree)			41.47	41.44
						ce that extraposition contexts
	are over Eall'	easiëi9brahe	rifidel to reso	lve, regar	dless o	f the syntactic position of the
	verb under	scrutiny.	9	6.49 9	93.04	78.50
	Ran	dom Baseline	4	2.54	41.48	41.44

4 Conclusion

References

1. Devlin, J., Chang, M.W., Lee, K., Toutanova, K.: BERT: Pre-training of deep bidirectional

Summary, Discussion

- Dutch BERT does not seem to inherently capture verb-subject dependencies very well (in verb clusters),
- Specific verb categories introduce their own complexity to the model (extraposition vs raising vs control),

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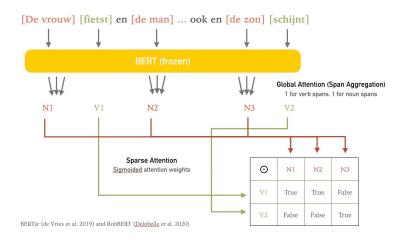
What's next

Going multilingual, using the same abstract syntax to generate surface forms in several languages, e.g.

lk weet dat	Jan	Marie	de kinderen	ziet	leren	fietsen
Ich weiß dass	Jan	Marie	die Kinder	fahren	lernen	sieht
I know that	John	sees	Mary	teach	the children	to cycle

▷ Challenge: finding the appropriate (aligned) training data

Probing ellipsis



Reference

Tessel Haagen, Loïs Dona, Sarah Bosscha, Beatriz Zamith, Richard Koetschruyter, Gijs Wijnholds. Noun Phrase and Verb Phrase Ellipsis in Dutch: Identifying Subject-Verb Dependencies with BERTje. Computational Linguistics in the Netherlands 2022.

Back to the bigger picture

Take away

- ► Large-scale Language Models are a staple in the NLP toolkit, despite limited knowledge about their 'intelligence'.
- ▶ Using techniques from formal grammar, we can show that they have limited capabilities for linguistic 'understanding'.

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Going further

- Compositional generalization: how can LMs generalize, e.g. on objectives like negation, monotonicity? Yanaka et al. [2019], Wijnholds [2023]
- Data/scale: what can we do about data bias, pretraining objectives, to create more efficient models?
- Hybrid models: in what way can we harness the power of LMs and combine them formal representations?

The robots are not coming (yet)

		onderwerp van fietsen?
	\$	In de zin "Ik weet dat de docent de student de hond zag leren fietsen", is de hond het onderwerp van fietsen.
	GI	In de zin "Ik weet dat de docent de student de hond zag leren fietsen", wie is het onderwerp van leren?
	\$	In de zin "Ik weet dat de docent de student de hond zag leren fietsen", is de hond het onderwerp van leren.
	GI	In de zin "Ik weet dat de docent de student de hond zag leren fietsen", wie is het onderwerp van zag?
	\$	In de zin "Ik weet dat de docent de student de hond zag leren fietsen", is de docent het onderwerp van zag.
		S Regenerate response
		>
ChatG	PT Jan 9	Version Free Research Preview. Our goal is to make Al systems more natural and safe to interact with. Your feedback will help us improve

In de zin "Ik weet dat de docent de student de hond zag leren fietsen", wie is het

Thank you!

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Github references

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for the MCFG generation and prober evaluation

https://github.com/gijswijnholds/malin_2022

for the ACG style generation and prober evaluation

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