Syntax and grounding in adjective learning

Adèle Hénot-Mortier (MIT)

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Queen Mary University of London

Introduction

Which factors enable word learning in humans?

"You shall **know** a word by the **company** it keeps".

J. R. Firth, *Studies in Linguistic Analysis*, 1957

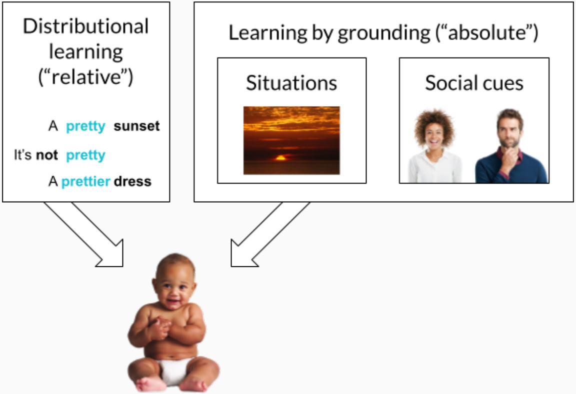
- Distributional Hypothesis (Harris, 1954): words with similar **syntactic environments** have similar **meanings**.

An example of distributional learning

- Distributions encode a lot of information, but comes with challenges!

Sunsets are **so**	**pretty**	
The **red dress** is	**pretti-**	**er** than the **blue** one
Jo finds **Crocs**	**pretty**	
Anglerfish do **not** look	**pretty**	
This is a	**pretty**	**ugly** way to say it

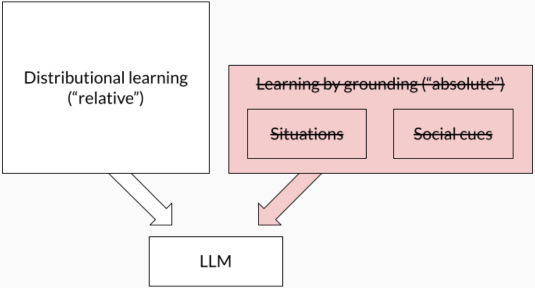
Human word learning results from entangled factors



- Both distributional cues[1] and grounding are used for word learning in humans, but these factors are **hard to disentangle**!

[1] L. R. Gleitman, 1981; L. Gleitman, 1990; Naigles, 1990; Snedeker and Gleitman, 2004; Syrett, 2007; Yuan et al., 2012; Gotowski, 2022.

LLMs can help determine the limits of distributional learning



- **L**arge **L**anguage **M**odels, (LLMs) **typically do not display grounding**.[2] They therefore represent an interesting edge case re:

How far can distributional information alone take us?

[2]Cf. Bender and Koller (2020) for a position paper. Multimodal LLMs exist however (Alayrac et al., 2022 i.a.), and may arguably display more grounding. For this reason they appear less relevant to our research question.

Plan for today

Plan for today

- **Two case studies** focusing on **adjective learning**.
- They vary in **how much distributional information** can be used by LLMs to distinguish adjectives.
- **Successes or failures** inform us re:

How far can distributional information alone take us?

The two studies

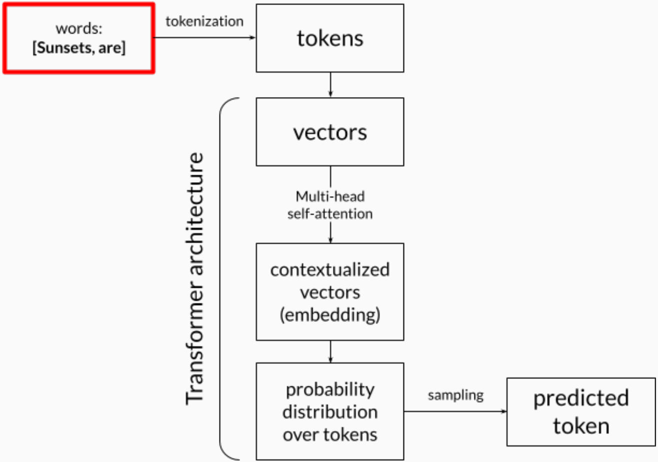
- **Study 1** focuses on the argument structure of adjectives like **tough**, **pretty**, **brave**, and **short**.
  - The observed distinctions are **distributionally clear**...
  - but **intuitively subtle**.
- **Study 2** focuses on antonymic adjectives (e.g. **tall**/**short**) an their behavior under negation.
  - The observed distinction is **intuitively obvious**...
  - but **distributionally subtle**.

Methods

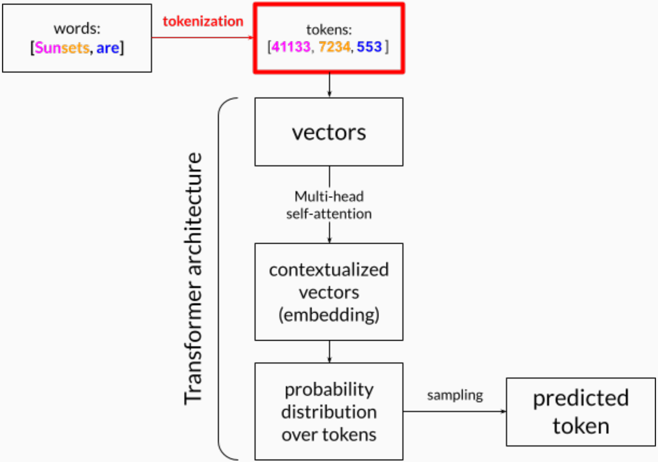
Structure of both studies

- Two kinds of “assessment”, inspired by psycholinguistics.
- **“Behavioral”:** are LLMs differentially “**surprised**” when processing contrasting sentences that only differ in the adjectives used?
- **“Neural”:** are the behavioral contrasts, rooted in the internal **vector** representations assigned by the models to the adjectives ?

A bird's eye view on LLMs' architecture



A bird's-eye view on LLMs' architecture



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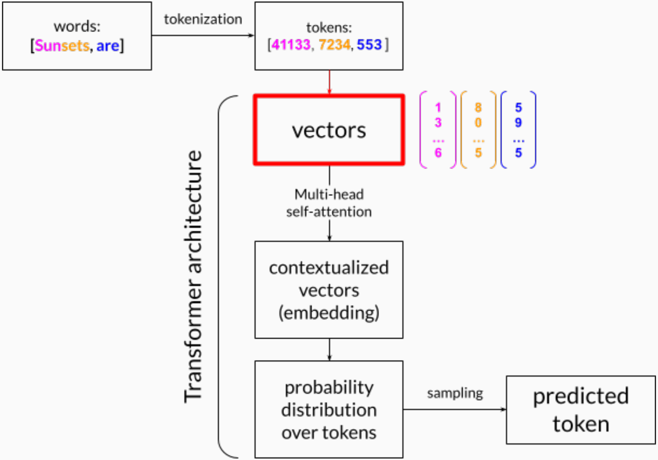

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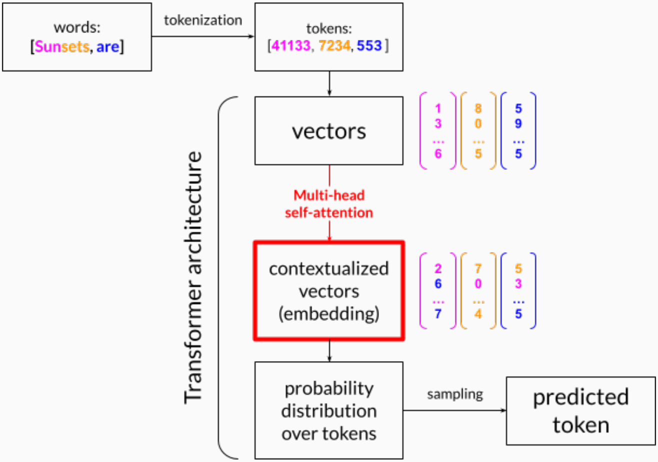

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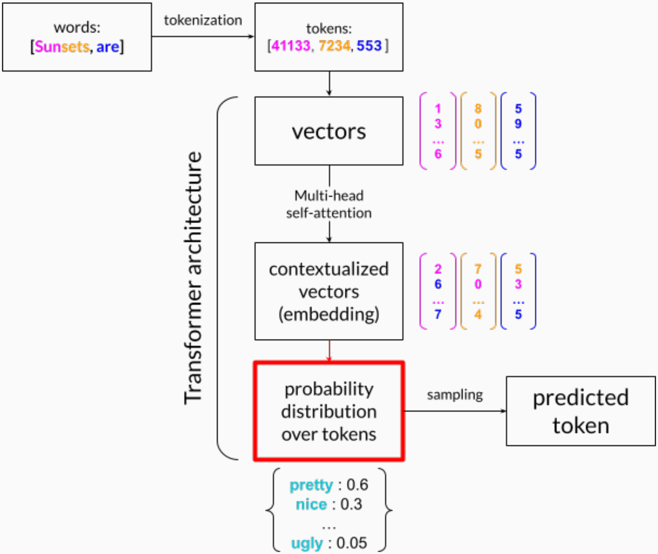

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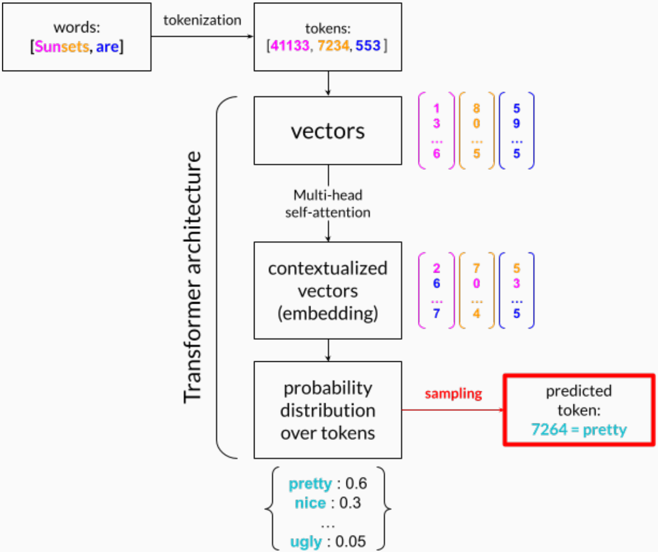
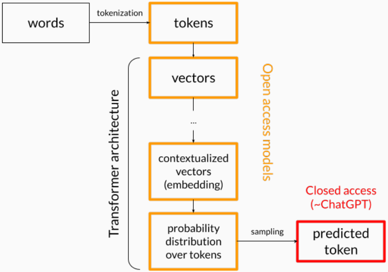


Models tested, and rationale

- Five Transformers: GPT-2, XLNet, BERT, RoBERTa, Mistral7B.[3]
- Though not state-of-the-art, **open-access**.
- Contrast with indirect prompting methods.[4]
- Allow to evaluate the **robustness** of the Transformer architecture.



- **Focus on the best-performing model, GPT-2.**

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[4]Vaswani et al., 2017; Devlin et al., 2018; Liu et al., 2019; Radford et al., 2019; Yang et al., 2019; Jiang et al., 2023

[4]Hu and Levy (2023) shows that prompting and probability assessment can yield significantly different outcomes.

Study 1

Distinguishing adjectives through their syntactic distribution.
Code; Surprisal dataset.

Learning to distinguish categories of adjectives

- It seem hard to distinguish adjectives like **short**, **tough**, **pretty**, and **brave** at first blush.

(1) a. This problem is **short**/**tough**/?**pretty**/*__brave__.
  b. Jo is **short**/**tough**/**pretty**/**brave**.
  c. This decision is ***short**/**tough**/***pretty**/**brave**.

- **The Distributional Hypothesis can help**: **short**, **tough**, **pretty**, and **brave** can be easily and sharply teased apart in terms of their syntactic distributions.[5]

[5] Supported by syntactic theory: cf. Rosenbaum (1967), Lasnik and Fiengo (1974), Stowell (1991), and Keine and Poole (2017), among many others.

Differences in terms of clausal embedding

- **Short**-like adjectives cannot embed an **infinitival clause**, while the other adjectives can.

(2) **This X is A to VP**

a. * This kid is **short**/**old**/**poor** to ride the rollercoaster.

b. This problem is **tough**/**interesting**/**impossible** to solve.

c. This vase is **pretty**/**harmonious** to look at.

d. This student is **brave**/**rude**/**smart** to point out the issue.

Differences in the availability of an "impersonal" variant

- **Tough**- and **brave**-adjectives can take a **dummy** *it* as subject, while **pretty**- and **short**-like adjectives can't.

(3) **It's Adj to VP**

a. **It**'s **tough** to solve this problem.

b. **It**'s **brave** to point out the issue.

c. * **It**'s **pretty** to look at this vase.

d. * **It**'s **short** to ride the rollercoaster.

Two refinements of the impersonal construction

- The impersonal **tough**-construction allows for an extra experiencer introduced by **for**.

(4) **It's Adj for X to VP**

a. **It**'s **tough** **for** Jo to solve this problem.
b. * **It**'s **brave** **for** Jo to point out the issue.
c. * **It**'s **pretty** **for** Jo to look at this vase.
d. * **It**'s **short** **for** Jo to ride the rollercoaster.

- The impersonal **brave**-construction, allows for an extra theme introduced by **of**.

(5) **It's Adj of X to VP**

a. * **It**'s **tough** **of** Jo to solve this problem.
b. **It**'s **brave** **of** Jo to point out the issue.
c. * **It**'s **pretty** **of** Jo to look at this vase.
d. * **It**'s **short** **of** Jo to ride the rollercoaster.

Four classes of adjectives, three contrasting templates

- Templates (2), (4) and (5) are sufficient to tease apart our adjectives.

Template		short	tough	pretty	brave
(2)	X is Adj to VP	*			
(4)	It's Adj for X to VP	*		*	*
(5)	It's Adj of X to VP	*	*	*	

- These distributional differences correlate with broad semantic differences.

Can LLMs leverage the distributional contrasts between these adjectives, to distinguish between them on psycholinguistics-inspired tasks?

Behavioral assessment

"Templatic" stimuli

- We focus on template (4).[6]

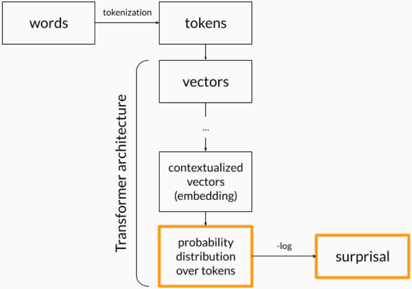
(4) It's $\left\{ \begin{array}{l} ^{\checkmark}\textbf{tough} \\ ^{\text{✗}}\textbf{short} \\ ^{\text{✗}}\textbf{pretty} \\ ^{\text{✗}}\textbf{brave} \end{array} \right\}$ for **you** to **rible** this **zud**.

- (4)+**tough** is **more grammatical** than (4)+{**short**, **pretty**, **brave**}.
- We filled (4) with 64 adjectives (16 per class), 3 experiencer pronouns, 7 nonce verbs, 7 object nonce nouns.

[6] Templates (2) and (5) were also tested.

Surprisal as a dependent variable

- The **surprisal** $\mathscr{S}$ of a sentence is its **negative log probability**.
- In humans, word surprisal correlates with processing effort.[7]
- In LLMs, **surprisal differences** may reflect **grammatical contrasts**.[8]



ungrammatical	$\sim$	**unlikely**	$\sim$	**surprising**
*		$p \simeq 0$		$\mathscr{S} = -\log(p) \simeq \infty$

[8]Hale, 2001; Levy, 2008

[8]See E. Wilcox et al. (2018), Futrell et al. (2019), and E. G. Wilcox et al. (2023). van Schijndel and Linzen (2021) and Arehalli et al. (2022) however suggest that LLM surprisal underestimates human slowdowns in garden-path effects.

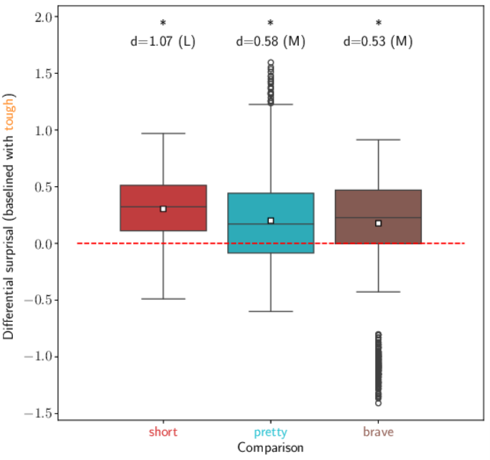
Prediction for template (4)

(4) It's $\left\{ \begin{array}{l} ✓\textbf{tough} \\ ✗\textbf{short} \\ ✗\textbf{pretty} \\ ✗\textbf{brave} \end{array} \right\}$ for **you** to **rible** this **zud**.

- In template (4), **tough**-adjectives should be the **least surprising.**

$$\mathscr{S}(\text{It's } \textbf{short}/\textbf{pretty}/\textbf{brave} \text{ for } \textbf{you} \text{ to } \textbf{rible} \text{ this } \textbf{zud}.)$$
$$-\ \mathscr{S}(\text{It's } \textbf{tough} \text{ for } \textbf{you} \text{ to } \textbf{rible} \text{ this } \textbf{zud}.)$$
$$> 0$$

Focus on GPT-2 and template (4)



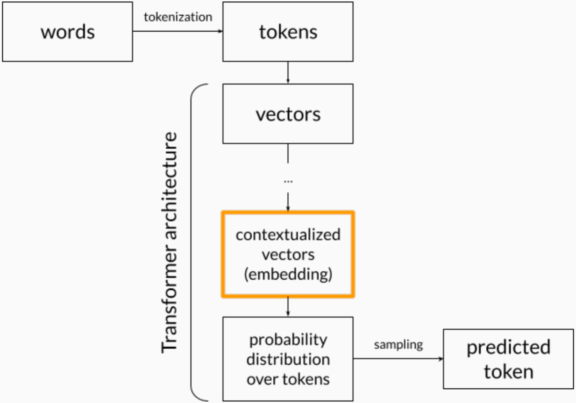
Differential surprisals (**short**, **pretty**, **brave** vs. **tough**) from GPT-2 Large. White squares display the means.

One-sided Wilcoxon test for matched pairs. *p*-values are Benjamini-Yekutieli-corrected. Effect sizes are Cohen's *d*. M=Medium, L=Large.

Neural assessment

What are LLMs' "neural" representations?

Does the "surprise" of LLMs correlate with their internal representation of the relevant adjectives?



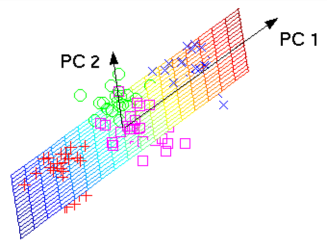
Rationale behind embeddings

- Pre-LLM embeddings have been shown to capture semantic relations between words, e.g. analogies of the form "*king* - *man* + *woman* = *queen*".[9]
- Do the embeddings derived by our LLMs reflect a distinction between **tough**, **pretty**, **brave**, and **short**-like adjectives, in terms of **vector clustering**?

[9] Mikolov, Chen, et al., 2013; Mikolov, Sutskever, et al., 2013; Pennington et al., 2014.

Methodology

- Vectors extracted from the LLMs' penultimate layer and reduced via Principal Component Analysis (**PCA**).
- PCA **kills uninformative dimensions**.



GPT-2's internal representations

Successes of Study 1

- **Distributional information seems sufficient** to derive meaningful distinctions between **different categories of adjectives**.
- The models' performance contrasts with that of humans:
  - A classification of these adjectives in terms of e.g. polarity or subjectivity may seem more intuitive.
  - Some classes of adjectives appear in constructions that are comparatively late-acquired.[10]
- Did LLMs **learn something brand new**, or were they able to **efficiently encode** a pattern fully present in the input?
- We now investigate **another distinction between adjectives**, that is more primitive, but also more challenging to learn from a purely distributional perspective.

[10] Chomsky, 1969.

Study 2

Distinguishing antonymic adjectives through their behavior under negation.

Code; Surprisal dataset

Antonymic adjectives and the Distributional Hypothesis

- The opposition between positive and negative adjectives is **easy to learn** from an early age.[11]
- But antonyms occur in **very similar distributions**![12]
- Earlier neural networks could not capture anonymity.[13].

[11] Clark, 1972; Jones and Murphy, 2005.
[12] Charles and Miller, 1989; Justeson and Katz, 1991.
[13] Aina et al., 2019.

Positive and negative adjectives lead to distinct inferences

(6) a. Jo is **not** **tall**. $\rightsquigarrow$ Jo is fairly **short**.
"Inference Towards the Antonym" (ITA)[14]

b. Jo is **not** **short**. $\not\rightsquigarrow$ Jo is fairly **tall**.

- The ITA requires to "understand" the difference between **positive** and **negative** adjectives, and their interaction with negation, **in the absence of clear distributional cues**.

Why would LLMs be better than earlier models to learn these challenging distinctions?

[14]Horn, 1989; Krifka, 2007; Ruytenbeek et al., 2017; Gotzner et al., 2018.

Behavioral assessment

Operationalizing the ITA contrasts in terms of surprisal

- The template in (7) captures ITA contrasts in terms of felicity.[15]

(7) a. He is not **tall**. She too is **short**.
Presupposes: not **tall** $\sim$ **short**.

b. # He is not **short**. She too is **tall**.
Presupposes: not **short** $\sim$ **tall**.

- These pairs allow us to reuse the "**differential surprisal**" methodology from Study 1.

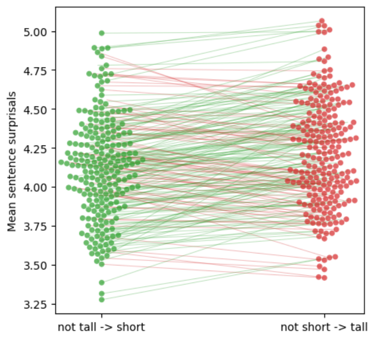
$$\mathscr{S}(\text{7b}) - \mathscr{S}(\text{7a}) > 0$$

- 111 antonymic pairs were used to measure this difference.

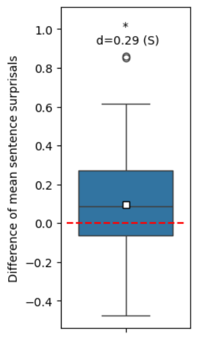
[15] Inspired by Ruytenbeek et al. (2017). Two other templates were tested, one where *too* appears after the second adjectives, and one "meta" template using the predicate *mean* to coordinate the two sentences.

Results for GPT-2

Hypothesis: $\mathscr{S}$(7b) - $\mathscr{S}$(7a) > 0



Surprisals of (7a) and (7b). Lines indicate minimal pairs. Green lines are ascending, i.e. are the ones for which the surprisal difference goes in the expected direction. Red lines are descending, and so go in the opposite direction.



Paired differences in surprisal between (7b) and (7a). White squares display the means.

One-sided Wilcoxon test for matched pairs. Effect size is Cohen's *d*. S=Small.

Refining the ITA

- LLMs display surprisal contrasts that suggest they learned something about adjective polarity.
- Some antonyms, like **lucky**/**unlucky**, are **morphologically transparent**, and as such give rise to bigger ITA contrasts.[16]

(8) a. He is not **lucky**. She too is **unlucky**.

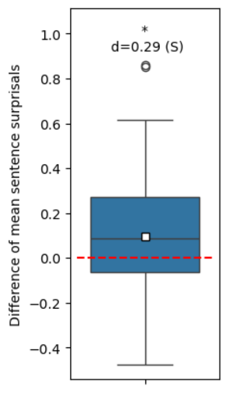
b. # He is not **unlucky**. She too is **lucky**.

- In such pairs, **polarity is distributionally encoded**, via a negative morpheme.

Can LLMs pick this up, and why would this matter?

[16] Ruytenbeek et al., 2017.

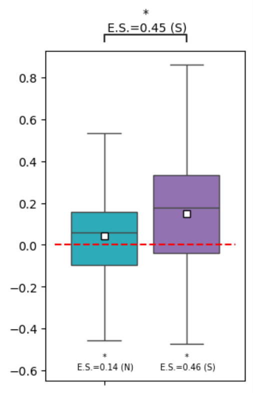
Results for GPT-2 (transparent vs. opaque)



Paired differences in surprisal between (7b) and (7a). All pairs together. White squares display the mean.

Splitting **transparent** (48) and **opaque** (63) pairs

➔

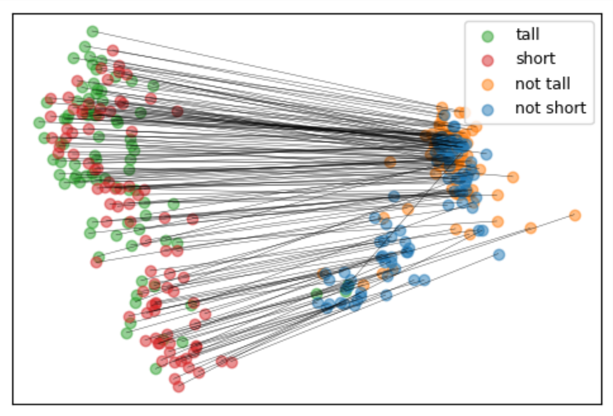


Paired differences in surprisal, **transparent** vs. **opaque** pairs.
White squares are means.Within-group p-values are BY-corrected. Effect size is Cohen's d. N=Negligible.

- The ITA contrast is verified only for **transparent** adjectives!

Neural assessment

GPT-2's Embedding



GPT-2's 2D embedding (obtained with PCA). If a word was made of multiple tokens, its vector was computed as the mean of its tokens' vectors. Lines between points track the effect of negation, that is fairly stable, i.e. not contextualized.

- Antonyms and their negations cluster together!

Study 2 outlines the limits of distributional learning

- The ITA was only captured **when adjectives contained distributional information** (negative morphemes) indicating their polarity.
- Additionally, **the embedding space was characterized by counterintuitive topological regularities**, suggesting the functional nature of negation was not captured.
- This behavior contrasts with our intuitive understanding of antonyms, that we grasp from early toddlerhood, even for opaque pairs like **tall** and **short**.

Main takeaways from the Studies

- The two studies allow to disentangle the importance of **grounding** from that of **distributional information**, in the context of adjective learning.
- LLMs succeed if, and only if, **distributional cues are explicit and local enough**.
- Their performance on the target phenomena **sharply contrasts with children's acquisition of adjectives, and adult intuitions.**
- This suggests that grounding an social cues are crucial for word learning, even when the goal to simply distinguish between meanings.

Zooming out: why these findings matter

- Study 1 and 2 point to important differences in the **environments** in which human and machine are learning, offering insights into:
  - **Human learning**: how much do linguistic biases, and extra-linguistic factors matter for language acquisition?
  - **Machine learning**: where should our efforts lie in improving the models?

Zooming out: fostering a productive interdisciplinary dialogue

- The tools presented today provide a **new type of testbed** for a number of questions that **matter to linguists**.[17]
- The linguistic datapoints we investigated may also **benefit computer scientists** who design and train LLMs, stressing the need for more grounded, reliable, and robust models of natural language.

[17] Study 1 in fact emerged from prior theoretical and experimental work of mine Hénot-Mortier et al., 2022; Hénot-Mortier, submitted

Thank you !

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Appendices

Links to Appendix slides

- General supplementary slides
- Supplementary slides Study 1
- Supplementary slides Study 2

Some extra background on positive and negative adjectives

- It has been observed that intuitively positive vs. negative adjectives pattern differently in several respects...
  - Positive (rather than negative) adjectives are used to **ask unbiased degree-related questions**.
  - Positive (rather than negative) adjectives are used to **form unbiased comparatives/equatives**.
  - Negative (rather than positive) adjectives may **feature overt negative morphology**.

(9) a. How tall is John? $\rightsquigarrow$ John may be tall or short.

b. How short is John? $\rightsquigarrow$ John is short.

(10) a. John is as tall as Paul. $\rightsquigarrow$ Both may be tall or short.

b. John is as short as Paul. $\rightsquigarrow$ Both are short.

(11) a. in-competent; im-modest; un-lucky; dis-honest ...

b. *un-small; *im-messy; *un-poor; *dis-arrogant ...

Testing "paradigms"

- 3 kinds of minimal pairs were assessed in 3 different sub-experiments. All pairs of sentences were counterbalanced for gender and filled with the 111 possible (**A^+**, **A^-**) antonymic pairs.

(7′) "Postposed *too*" (very close to the stimuli in Ruytenbeek et al., 2017)

a. He is not **A^+**, and she is **A^-** too.

b. # He is not **A^-**, and she is **A^+** too.

(7″) "Preposed *too*" (does more justice to left-to-right LLMs)

a. He is not **A^+**. She too is **A^-**.

b. # He is not **A^-**. She too is **A^+**.

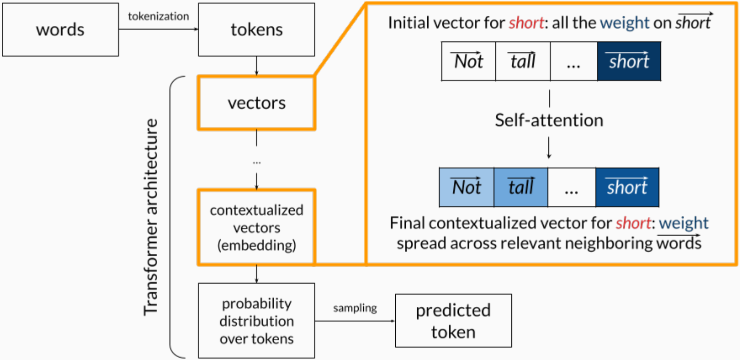
(12) "Meta"

a. He is not **A^+** means that he is **A^-**.

b. # He is not **A^-** means that he is **A^+**.

Self-attention creates context-sensitive word representations

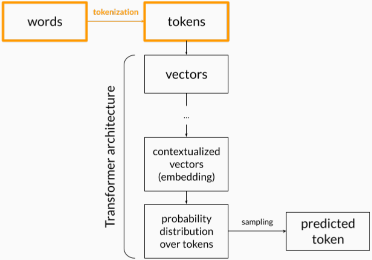
- **Self-attention** is at the core of Transformers, and should allow them to grasp the **contextualized meaning** of antonymic adjectives, and the **functional behavior** of negation.[18]



[18]Though see Peng et al. (2024).

Tokenization as a proxy for morphological decomposition

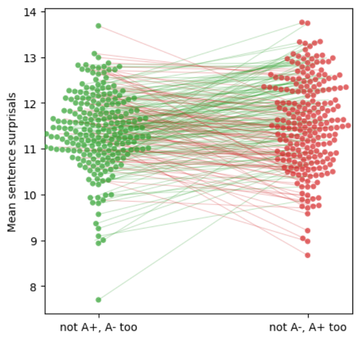
- **Tokenization** maps sentences into tokens, which represent words or pieces of words.
- Tokens are determined based on **character coocurrences**.
- Tokens may therefore reflect **morphology**,[19] and provide LLMs with useful distributional cues to derive ITA contrasts.



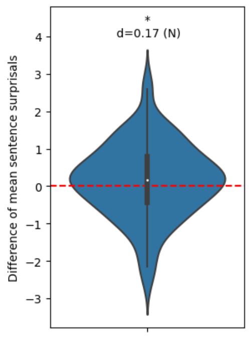
What happens when we focus on transparent vs. opaque pairs of antonyms?

[19]Nair and Resnik, 2023

Sentence-level results for XLNet (H1, preposed paradigm)



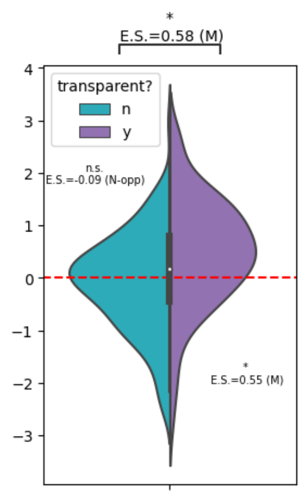
Surprisal pairings between between (8b) and (8a). Green links are the ones for which the surprisal difference goes in the expected direction. Red links go in the opposite direction.



Paired differences in sentence surprisal between (8b) and (8a).
'*' means $p < .05$; effect size is Cohen's d.

- Significant yet negligible effect with XLNet.

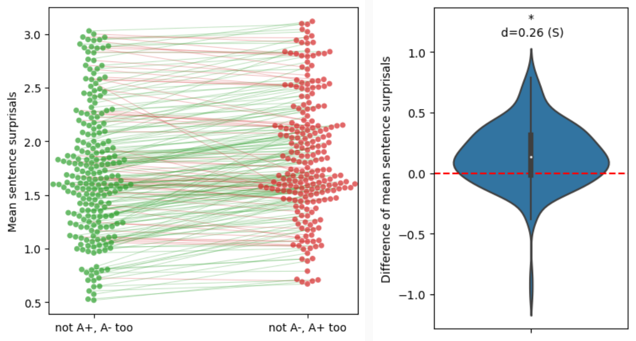
Sentence-level result for XLNet (H2)



Paired differences in surprisal between (8b) and (8a), depending on morphological transparency. Within-group *p*-values are BY-corrected.

- Morphologically transparent pairs are associated with a stronger contrast than opaque pairs.
- In fact, only the transparent group gives rise to a significant contrast in ITA.

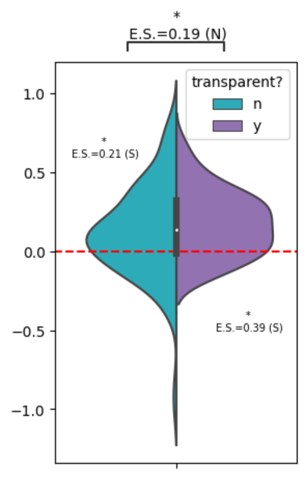
Sentence-level results for BERT (H1, preposed paradigm)



Paired differences in sentence surprisal between (8b) and (8a). '*' means $p < .05$; effect size is Cohen's d.

- Significant but small effect with BERT.

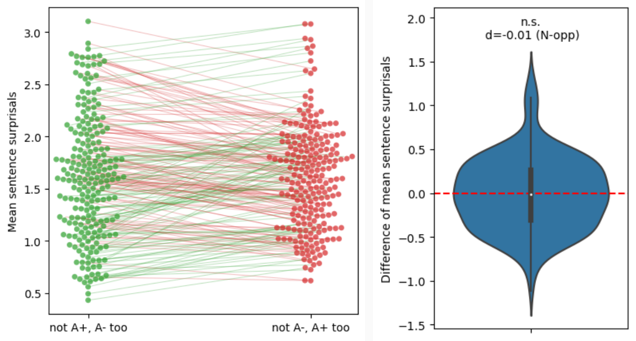
Sentence-level result for BERT (H2)



Paired differences in surprisal between (8b) and (8a), depending on morphological transparency. Within-group *p*-values are BY-corrected.

- No significant difference between morphologically transparent and opaque pairs.
- Significant, small contrast in ITA in both groups.
- So, the global ITA effect reported in the previous slide was driven equally by both groups.

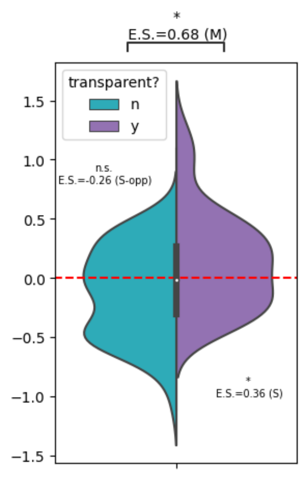
Sentence-level results for RoBERTa (H1, preposed paradigm)



Paired differences in sentence surprisal between (8b) and (8a).
'*' means $p < .05$; effect size is Cohen's d.

- Non-significant, negligible effect with RoBERTa.

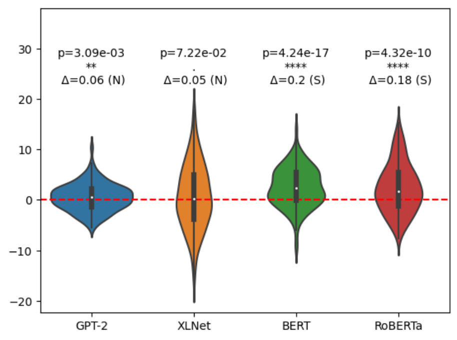
Sentence-level result for RoBERTa (H2)



Paired differences in surprisal between (8b) and (8a), depending on morphological transparency. Within-group *p*-values are BY-corrected.

- Morphologically transparent pairs are associated with a stronger contrast than opaque pairs.
- In fact, the transparent group gives rise to a significant contrast in ITA in the right direction, while the opaque group gives rise to a contrast, *in the wrong direction*!
- So, the absence of a global ITA effect reported in the previous slide was caused by the 2 groups counterbalancing each other.

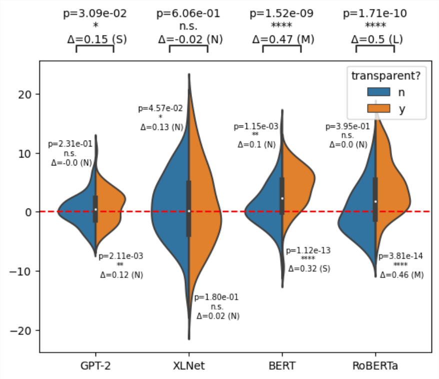
Sentence-level results for all models, postposed too paradigm



Paired differences in sentence surprisal between (5′b) and (5′a), *p*-value computed using a Wilcoxon test, effect sizes with Cliff's Δ.

- All models but one (XLNet) exhibit a significant contrast in ITA strength, but the effect sizes are negligible (GPT-2) or small (BERT/RoBERTa).
- Because *too* appears after the critical adjectives, this paradigm expectedly favors bidirectional models.

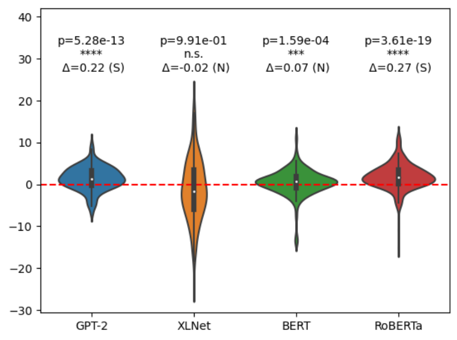
Postposed too paradigm at the sentence-level: group-by-group



Paired differences in sentence surprisal between (5′b) and (5′a), group-by-group (T vs. O), *p*-value computed using a Wilcoxon test, effect sizes with Cliff's Δ.

- BERT is the only model for which H1 is individually verified by both the T- and O-group.
- BERT also verifies H2, meaning, the T-group is associated to a bigger contrast in ITA strength than the O-group (medium effect size).

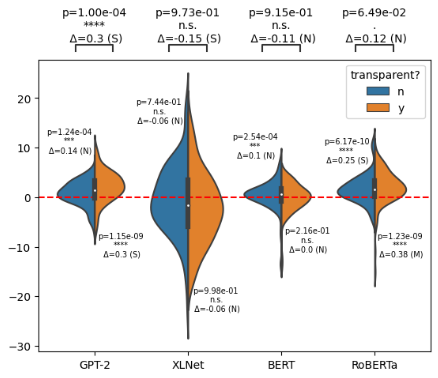
“Meta” paradigm at the sentence-level:both groups



Paired differences in sentence surprisal between (14b) and (14a), *p*-value computed using a Wilcoxon test, effect sizes with Cliff's Δ.

- All models but one (XLNet) exhibit a significant contrast in ITA strength, but the effect sizes are negligible (BERT) or small (GPT-2/RoBERTa).

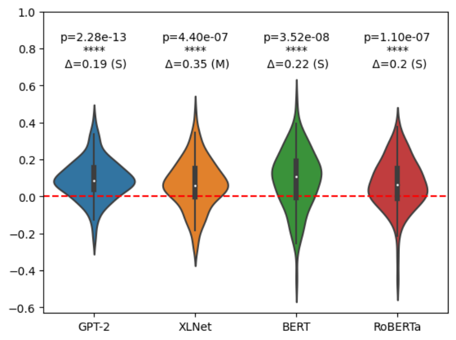
“Meta” paradigm at the sentence-level:group-by-group



Paired differences in sentence surprisal between (14b) and (14a), group-by-group (T vs. O), *p*-value computed using a Wilcoxon test, effect sizes with Cliff’s Δ.

- GPT-2 and RoBERTa are the two models for which H1 is individually verified by both the T- and O-group.
- But only GPT-2 clearly verifies H2 (RoBERTa is characterized by a negligible effect size...).

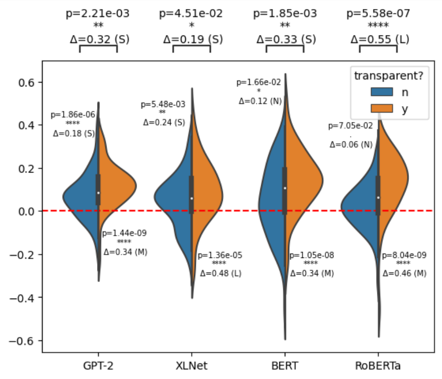
Results for H1, both groups



Paired differences in cosine similarities between $(\overrightarrow{\text{not } \mathbf{A}^{+}}, \overrightarrow{\mathbf{A}^{-}})$ and $(\overrightarrow{\text{not } \mathbf{A}^{-}}, \overrightarrow{\mathbf{A}^{+}})$, p-value computed using a Wilcoxon test, effect sizes using Cliff's Δ.

- All models exhibit a **significant contrast in cosine similarities (and by proxy ITA strength) as a function of adjective polarity**, with small-to-medium effect sizes.
- This suggests that H1 translates into a topological inequality within the LLMs' vector spaces!

Results for H1, group-by-group, and H2



Paired differences in cosine similarities between $(\overrightarrow{\text{not } \mathbf{A}^{+}}, \overrightarrow{\mathbf{A}^{-}})$ and $(\overrightarrow{\text{not } \mathbf{A}^{-}}, \overrightarrow{\mathbf{A}^{+}})$, group-by-group p-values computed using a Wilcoxon test, and between-group p-values using a Mann-Whitney U-test. Effect sizes are Cliff's Δ.

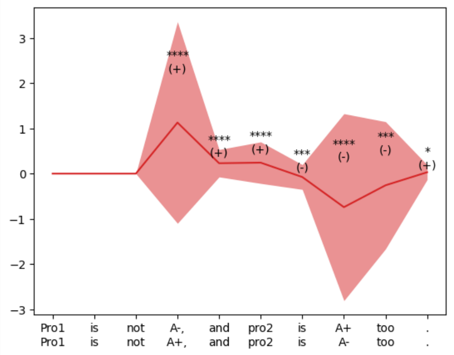
- GPT-2 and XLNet are the two models for which H1 is individually verified by both the T- and O-group.
- Both models also verify H2, meaning, the T-group is associated to a bigger contrast in ITA strength than the O-group (small effect sizes).
- **Quite encouraging results overall but...**

- **But what do the best performing models do at the word-level?**
- From a language processing standpoint, we expect the positive contrasts in surprisal witnessed in the sentence-level assessments to be **driven by the occurrence of the second adjective**:
  - given what precedes it, this adjective is expected to be ok (i.e. not surprising) when **negative**;
  - and less ok (i.e. quite surprising) when **positive**.

(7″) a. He is not $\mathbf{A}^{+}$. She too is $\mathbf{A}^{-}_{☺}$.

b. # He is not $\mathbf{A}^{-}$. She too is $\mathbf{A}^{+}_{☹}$.

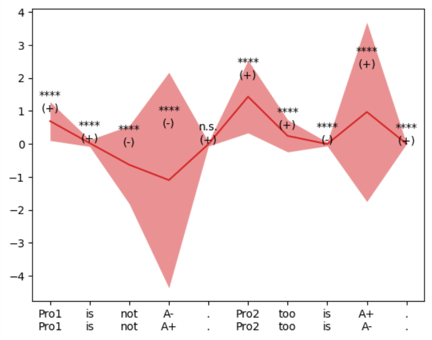
Word-level processing: GPT-2



Paired word-by-word differences in surprisal between (2″b) and (2″a), p-values computed using Wilcoxon tests. Red line is the mean, red enveloppe is the standard deviation. Similar plots for the two other paradigms.

- $\mathbf{A}^{-}$ is significantly more surprising than $\mathbf{A}^{+}$ after negation (position 4)...
- but also in position 8 (second occurrence), against the expectations...
- **The effect witnessed at the sentence-level was driven by the wrong element of the sentence!!!**
- BERT and RoBERTa did better but evaluating bidirectional models at the word-level is also trickier.

Word-level processing: BERT



Paired word-by-word differences in surprisal between (14b) and (14a), *p*-values computed using Wilcoxon tests. Red line is the mean, red enveloppe is the standard deviation. Similar plots for the two other paradigms.

- **A**$^{-}$ is significantly less surprising than **A**$^{+}$ after negation (position 4)...
- and also significantly less surprising than **A**$^{+}$ in position 9.
- The effect witnessed at the sentence-level makes sense at the word-level.
- But some amount of negative surprisal may have "transferred" from position 9 to position 4, due to the model's bidirectionality.

Measuring the ITA in the embedding space

- In this task, we abandon stimuli sentences to focus on the **internal (vector) representations assigned by the original standard LLMs to $\mathbf{A}^+$, $\mathbf{A}^-$, and their respective negations**: $\overrightarrow{\mathbf{A}^+}$, $\overrightarrow{\mathbf{A}^-}$, $\overrightarrow{\text{not } \mathbf{A}^+}$, $\overrightarrow{\text{not } \mathbf{A}^-}$.[2]
- A common measure of semantic proximity in such vector spaces is cosine similarity:

$$CosSim(\vec{v_1}, \vec{v_2}) = \frac{\vec{v_1} . \vec{v_2}}{||\vec{v_1}|| \times ||\vec{v_2}||} \in [-1; 1]$$

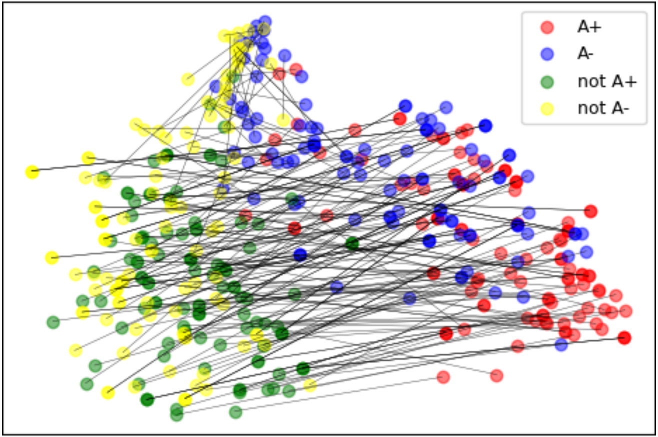
- If H1 translates into the LLMs' vector space, we then expect $\overrightarrow{\text{not } \mathbf{A}^+}$ to be closer to $\overrightarrow{\mathbf{A}^-}$ than $\overrightarrow{\text{not } \mathbf{A}^-}$ is close to $\overrightarrow{\mathbf{A}^+}$, i.e.:

$$CosSim(\overrightarrow{\text{not } \mathbf{A}^+}, \overrightarrow{\mathbf{A}^-}) - CosSim(\overrightarrow{\text{not } \mathbf{A}^-}, \overrightarrow{\mathbf{A}^+}) > 0$$

- Moreover, H2 predicts that this difference should be bigger for T-antonyms as opposed to O-antonyms.

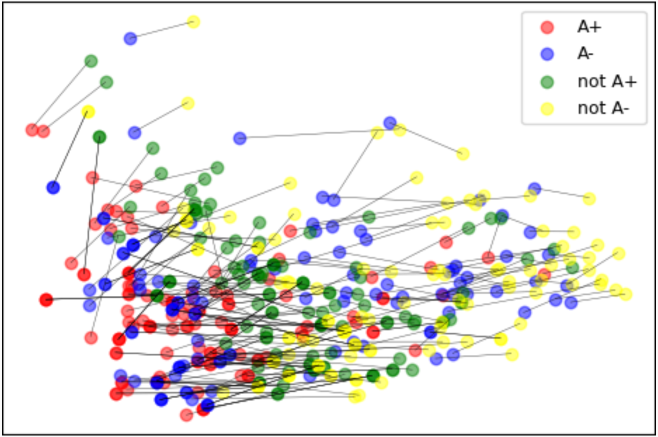
[2] In practice, we included the copula *is* as a left context to get those representations.

XLNet Embedding



XLNet

BERT Embedding



BERT