



Gridspace

GRIDSPACE IAP 2024 LECTURE 7  
Philosophy of Generative Linguistics vs. LLMs

January 29, 2024

# PLAN FOR TODAY

“a pair of docs talks about a paradox” - Anthony



# PLAN FOR TODAY



- **Why do we know *so much* when we know *so little*?**
  - Poverty of Stimulus / We don't know what we don't know
  - Implicit Knowledge / We don't know what we know
  - Universal Grammar / Why do we know
- **Why do LLMs know *so little* when they know *so much*?**
  - LLMs know what we don't know
  - LLMs don't know what we know
  - Learnability / Can LLMs learn grammar?

# PLAN FOR TODAY



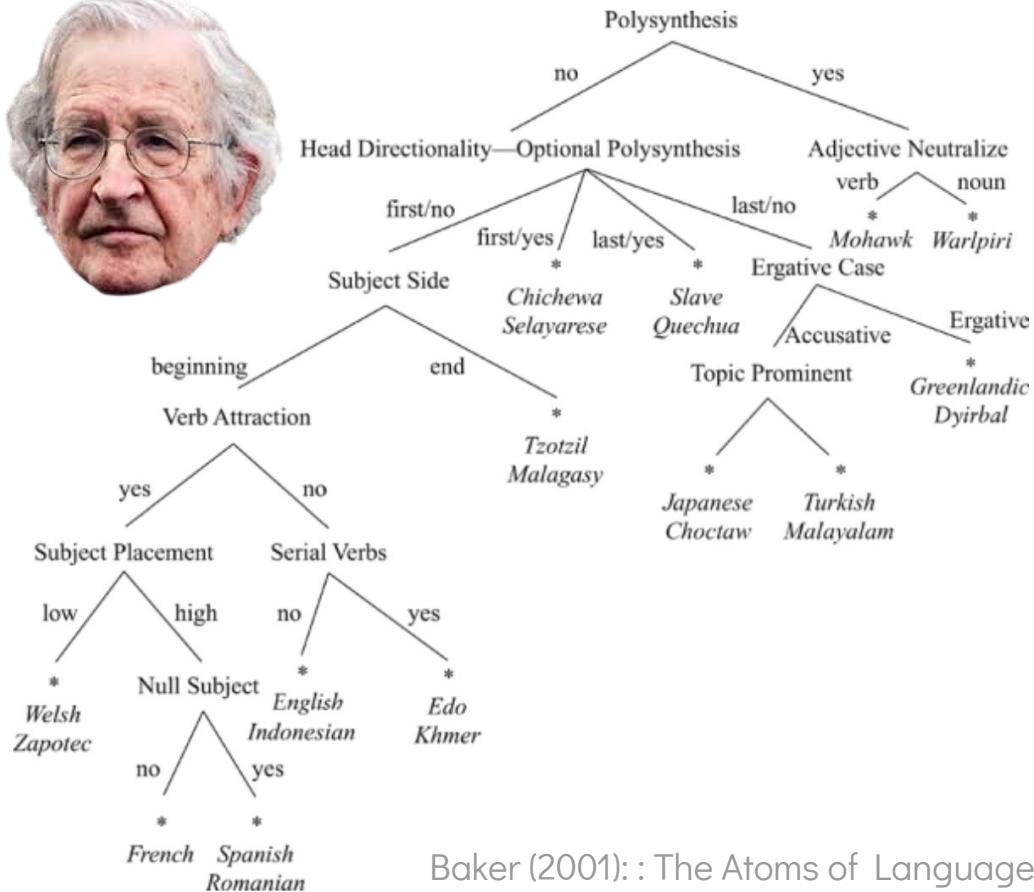
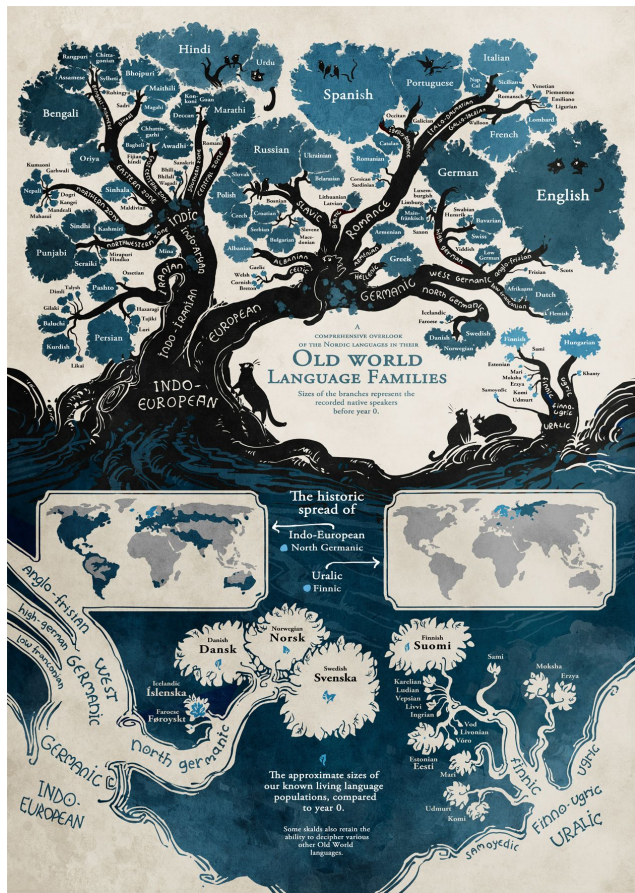
- LLMs *know grammar*
  - at least, I think so
- *Why* LLMs *can learn grammar*
  - Expressiveness of Transformer
  - Generalization -> Understanding
- LLMs *refute nothing*

# Philosophy of Generative Linguistics



<https://iep.utm.edu/chomsky-philosophy/>





Baker (2001): : The Atoms of Language,  
based on Chomsky (1981, 1986)

<https://www.theguardian.com/education/gallery/2015/jan/23/a-language-family-tree-in-pictures>

# Poverty of Stimulus

We don't know what we don't know



# Stimulus: Language data we're exposed to

I know *who* you met \_\_ yesterday.  
I know *that* you met Mary yesterday.

[+wh, +\_\_]  
[-wh, -\_\_]



based on Lan, Chemla & Katzir (2023)

\*I know *who* you met Mary yesterday.

\*I know *that* you met \_\_\_ yesterday.

\*[+wh, -\_\_]

\*[-wh, +\_\_]

→ Stimulus

based on Lan, Chemla & Katzir (2023)

\* *Who* will John's kissing \_\_\_ annoy you?  
*Who* will John's kissing \_\_\_ annoy \_\_\_?

Subject Island  
[+wh, +\_\_]

→ Stimulus

based on Lan, Chemla & Katzir (2023)

→ Stimulus

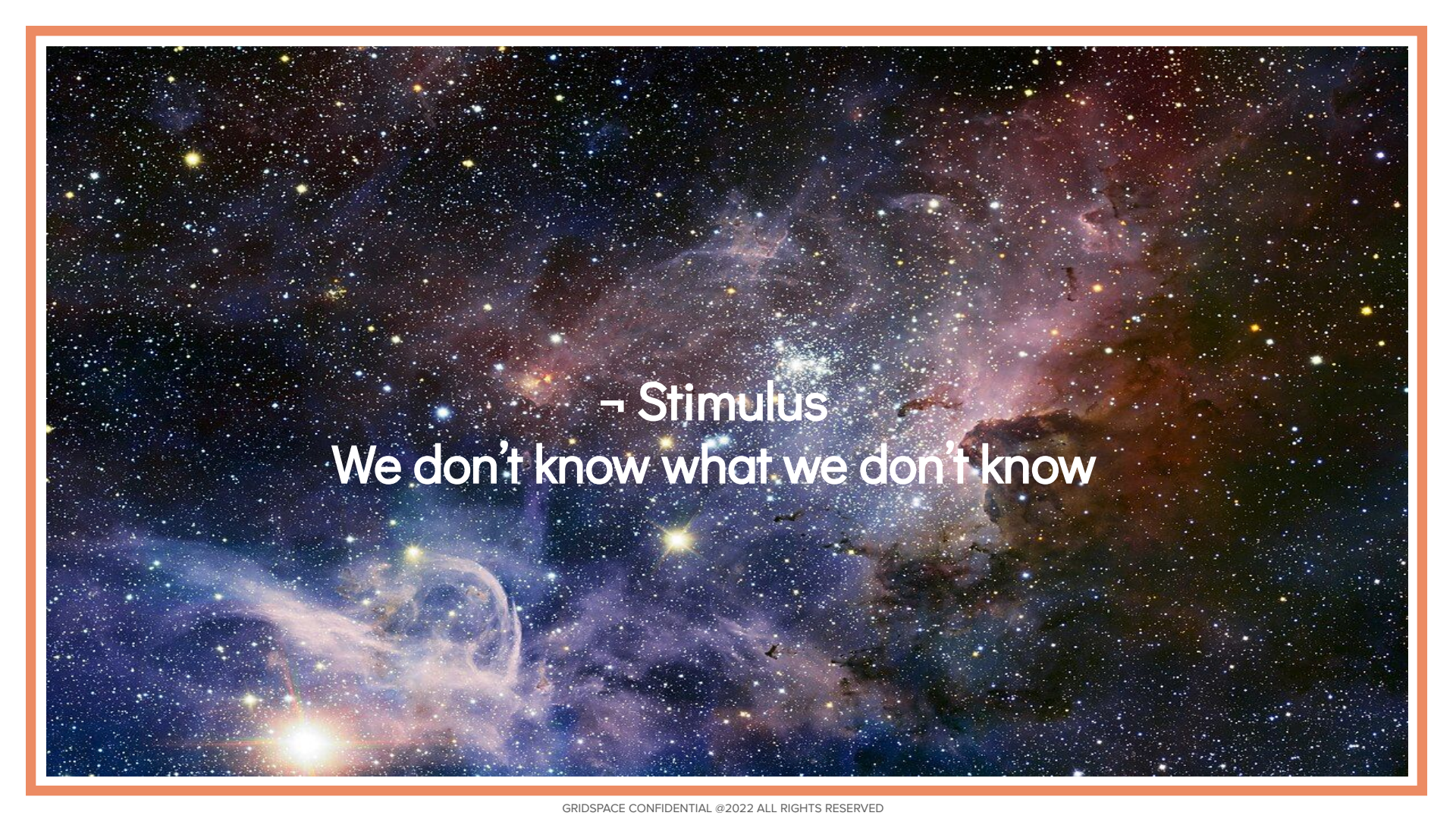
\*I wonder *who* John either kissed \_\_\_ or is going to kiss you.

I wonder *who* John either kissed \_\_\_ or is going to kiss \_\_\_.

CSC

[+wh, +\_\_]

based on Lan, Chemla & Katzir (2023)



– Stimulus  
We don't know what we don't know



Implicit Knowledge  
We don't know what we know

# Filler-Gap Dependency

	$+$ <u>        </u>	<u>        </u> $-$
$+wh$		*
$-wh$	*	

# Syntactic Islands

Filler-Gap Dependency is *Context-Sensitive*

## *Subject Island*

John's kissing Mary will annoy you.

\**Who* will [ John's kissing \_\_\_ ] annoy you?



# Syntactic Islands

Filler-Gap Dependency is *Context-Sensitive*

## *Coordinate Structure Constraint (CSC)*

I know John either kissed Mary or is going to kiss you.

\*I wonder *who* John *either* [ kissed \_\_\_ ] or [ is going to kiss you ].

# Syntactic Islands

Filler-Gap Dependency is *Context-Sensitive*

## *Complex Noun Phrase Island*

John heard the rumor that Mary kissed Tom.

\**Who* did John hear [ the rumor that Mary kissed \_\_\_ ]?

# Another Example

Another **F\*\*king** Example

F\*\*king Massachusetts  
F\*\*king Institute  
F\*\*king Technology



Massa-f\*\*king-chusetts

\*Ma-f\*\*king-ssachusetts

\*Massachu-f\*\*king-setts

,mæsə 'tʃu:sɪts

based on MIT 24.900 course material

\*In-f\*\*king-stitute

\*Insti-f\*\*king-tute

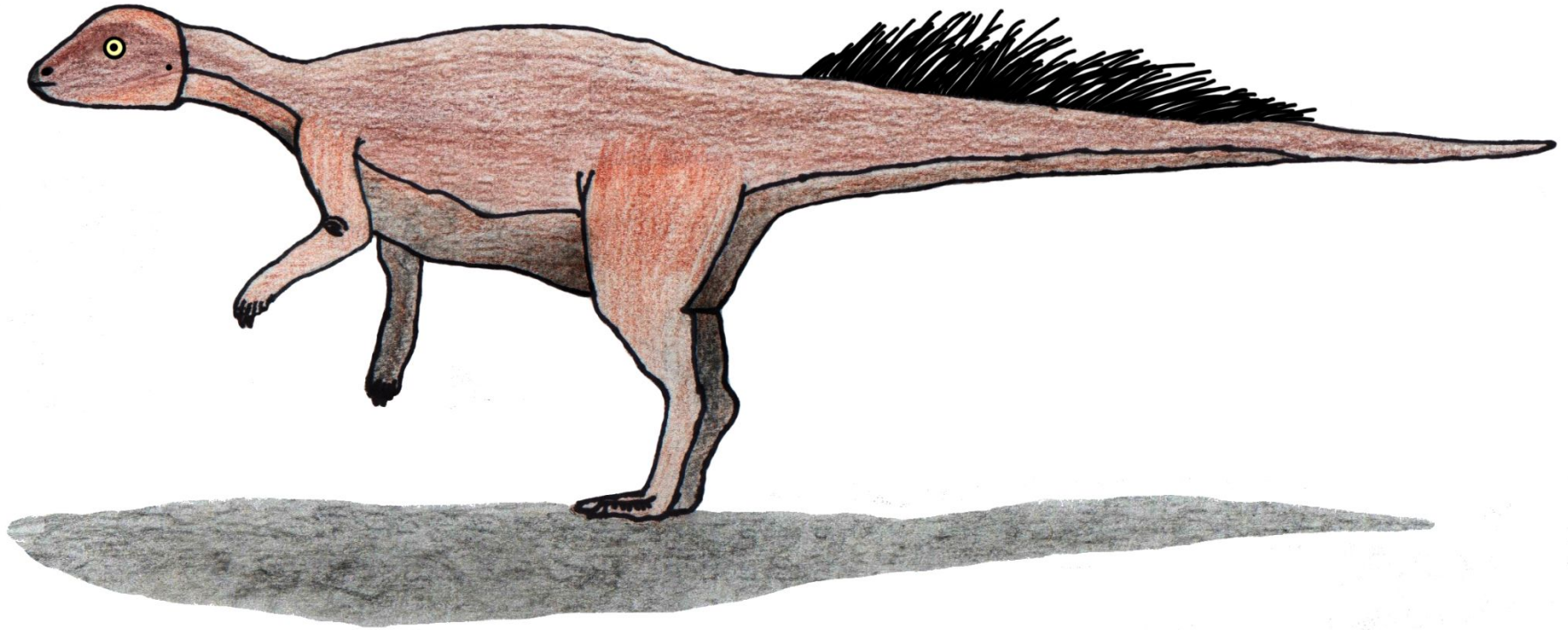
'instifju:t

based on MIT 24.900 course material

Tech-f\*\*king-nology  
\*Techno-f\*\*king-logy  
tɛk' nɒlədʒi

based on MIT 24.900 course material





[https://en.wikipedia.org/wiki/<name\\_of\\_dinosaur>](https://en.wikipedia.org/wiki/<name_of_dinosaur>)

?Micro-**f\*\*king**-pachycephalosaurus

?Micropachy-**f\*\*king**-cephalosaurus

Micropachycephalo-**f\*\*king**-saurus

ˌmaɪkroʊˌpæʃɪˌsɛfələˈsɔːrəs

IPA Credit: Vinita Cheepurupalli & Daniel Asherov



<https://allthingslinguistic.com/post/66913261919/expletive-infixation-from-xkcd-and-more>

We (as native speakers) know  
whether



is **grammatical or not** in the language we speak



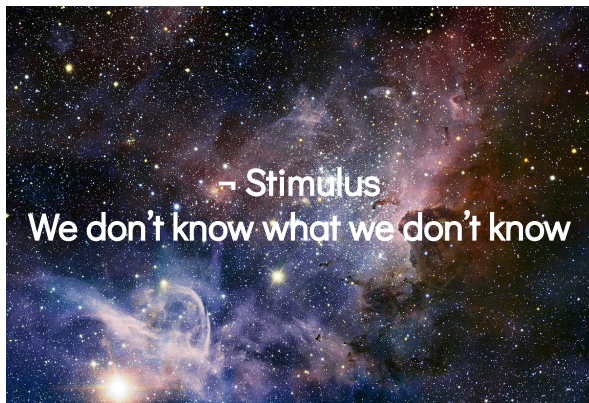
Why do we know?

# Universal Grammar

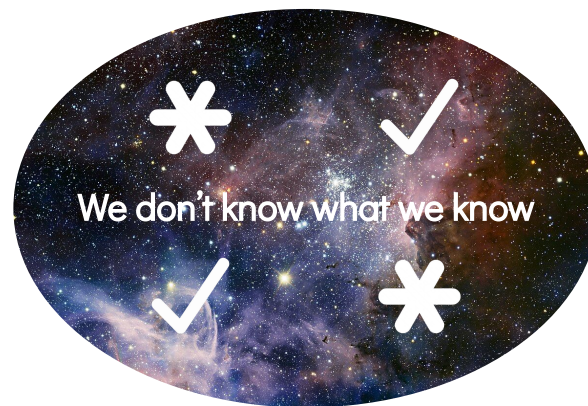
“The **innate knowledge** that humans have about language, which, under the right circumstances, enables them to acquire any particular language spoken around them.”



Baker (2001): The Atoms of Language



Poverty of Stimulus



Implicit Knowledge

- (1) S → NP + VP
- (2) VP → Verb + NP
- (3) NP → Det + N
- (4) Verb → Aux + V
- (5) Det → *the, a, ...*
- (6) N → *man, ball, ...*
- (7) Aux → *will, can, ...*
- (8) V → *hit, see, ...*



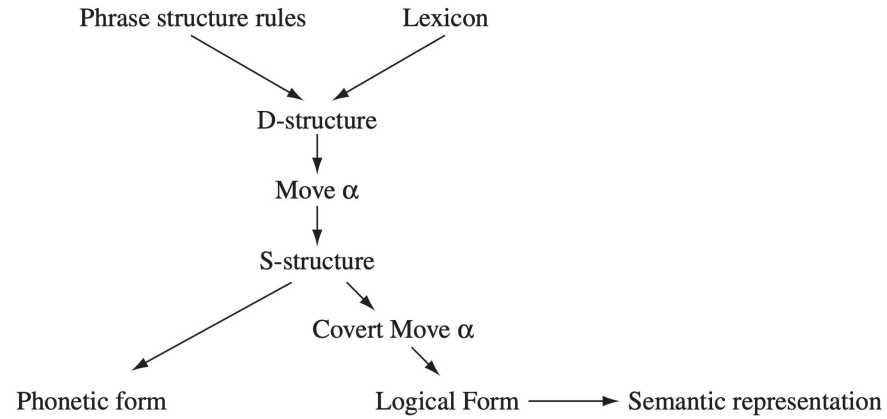
Chomsky (1957):  
Syntactic Structures



- (i) S
- (ii) NP + VP by rule (1)
- (iii) NP + Verb + NP by rule (2)
- (iv) Det + N + Verb + NP by rule (3)
- (v) Det + N + Verb + Det + N by rule (3)
- (vi) Det + N + Aux + V + Det + N by rule (4)
- (vii) *the* + N + Aux + V + Det + N by rule (5)
- (viii) *the* + N + Aux + V + *the* + N by rule (5)
- (ix) *the* + *man* + Aux + V + *the* + N by rule (6)
- (x) *the* + *man* + Aux + V + *the* + *ball* by rule (6)
- (xi) *the* + *man* + *will* + V + *the* + *ball* by rule (7)
- (xii) *the* + *man* + *will* + *hit* + *the* + *ball* by rule (8)

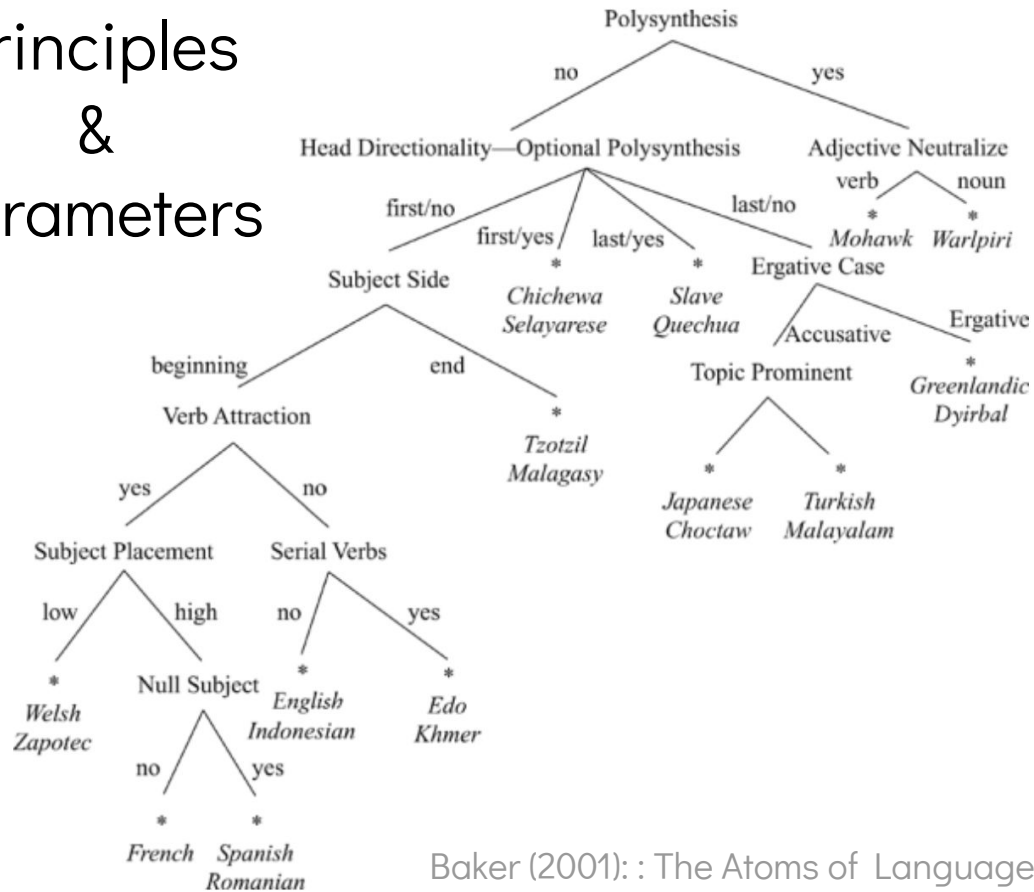
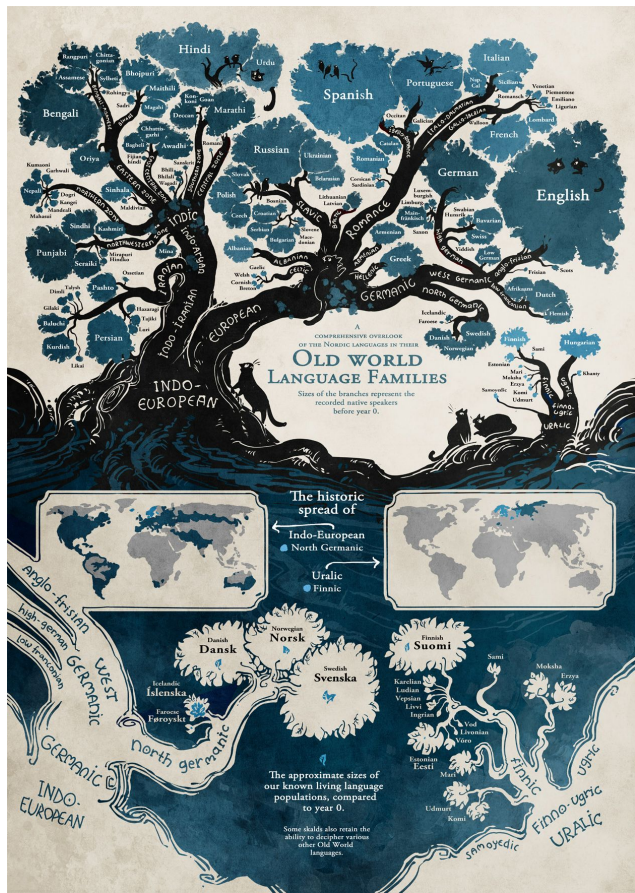


## Chomsky (1957): Syntactic Structures



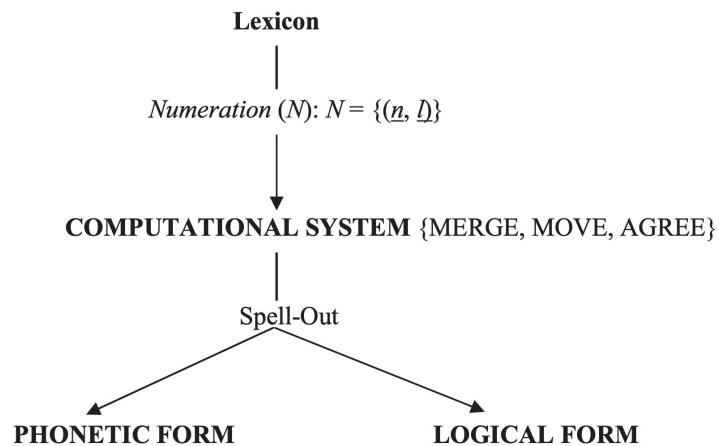
Chomsky (1981):  
Lectures on Government and Binding

# Principles & Parameters



Baker (2001): : The Atoms of Language, based on Chomsky (1981, 1986)

<https://www.theguardian.com/education/gallery/2015/jan/23/a-language-family-tree-in-pictures>



Chomsky (1995):  
The Minimalist Program

What do LLMs know about language?

LLMs know what we don't know

# GPT-3 Training Data: 570 GB

Dataset	Quantity (tokens)	Weight in training mix	Epochs elapsed when training for 300B tokens
Common Crawl (filtered)	410 billion	60%	0.44
WebText2	19 billion	22%	2.9
Books1	12 billion	8%	1.9
Books2	55 billion	8%	0.43
Wikipedia	3 billion	3%	3.4

**Table 2.2: Datasets used to train GPT-3.** “Weight in training mix” refers to the fraction of examples during training that are drawn from a given dataset, which we intentionally do not make proportional to the size of the dataset. As a result, when we train for 300 billion tokens, some datasets are seen up to 3.4 times during training while other datasets are seen less than once.

<https://www.linkedin.com/pulse/chatgpt-dall-e-2-show-me-data-sources-dennis-layton>

# GPT Context Window







<b>Model</b>	<b>Context Window (Tokens)</b>	<b>Approx. Words</b>	<b>Approx. Pages<sup>1</sup></b>	<b>Key Features</b>
GPT-4 (0613)	8,000	~6,000	~24	Balanced for depth and breadth of context; suitable for a wide range of tasks.
GPT-4 Turbo 128K	128,000	~96,000	~300	Larger context window for handling extensive interactions; ideal for processing large documents.
ChatGPT Plus	4,096 or 8,000 <sup>2</sup>	~3,072 or ~6,000	~12 or ~24	Enhanced accessibility and response speed; general access even during peak times.

<https://www.linkedin.com/pulse/maximizing-ai-potential-role-context-window-chatgpt-hatzilamprou-nfydf>



LLMs don't know what we know

# GPT Meets Syntactic Islands

	Subject Island	CSC	Complex NP Island
gpt-3.5-turbo			
gpt-4			

but see Wilcox, Futrell & Levy (2022)

# Subject Island: gpt-3.5-turbo 🙄🤔

**USER** (1) John's kissing Mary will annoy you.

Can I query the identity of Mary in (1) by asking

(2) Who will John's kissing annoy you?

**ASSISTANT** Yes, you can query the identity of Mary in (1) by asking (2) "Who will John's kissing annoy you?"

**USER** Is (2) a grammatical sentence?

**ASSISTANT** Yes, (2) is a grammatically correct sentence. It is an interrogative sentence in the form of a relative clause, asking for the identity of the person who will be annoyed by John's kissing.

**Who is the person that John's kissing \_\_ will annoy\_\_?**

Model

gpt-3.5-turbo

Temperature

1

Maximum length

256

Stop sequences

Enter sequence and press Tab

Top P

1

Frequency penalty

0

Presence penalty

0

# Subject Island: gpt-4 😊🤔

**USER** (1) John's kissing Mary will annoy you.

Can I query the identity of Mary in (1) by asking

(2) Who will John's kissing annoy you?

**ASSISTANT** No, you cannot construct the question that way. A better way to ask this question might be: "Who is the Mary that John's kissing will annoy you?" However, this question is still a bit awkward and presumptive. A more neutral way to ask might be: "Who is Mary, the one that John is kissing?" Then, in a separate question, you could ask whether this situation annoys the person: "Does it annoy you that John is kissing Mary?"



Model

gpt-4

Temperature

1

Maximum length

256

Stop sequences

Enter sequence and press Tab

Top P

1

# Coordinate Structure Constraint: gpt-3.5-turbo 😊

**USER** (3) I know John either kissed Mary or is going to kiss you.

Can I query the identity of Mary in (3) by saying

(4) I wonder who John either kissed or is going to kiss you.

---

**ASSISTANT** Yes, you can query the identity of Mary in (3) by saying (4). Your query in (4) implies that you are uncertain about who John either kissed or is going to kiss, and you want to find out who Mary is in this context.

---

**USER** Is (4) a grammatical sentence?

---

**ASSISTANT** No, I apologize for the mistake in my previous response. (4) is not grammatically correct. A more appropriate and grammatically correct way to phrase the query would be:

(4) I wonder who John either kissed or is going to kiss, including you.

This version of the sentence clarifies that you are wondering about the identities of both Mary and yourself.

Model

gpt-3.5-turbo

Temperature

1

Maximum length

256

Stop sequences

Enter sequence and press Tab

Top P

1

Frequency penalty

0

Presence penalty

0

🔒 API and Playground requests will not be used to train our models. [Learn more](#)

# Coordinate Structure Constraint: gpt-4 😊

**USER** (3) I know John either kissed Mary or is going to kiss you.

Can I query the identity of Mary in (3) by saying

(4) I wonder who John either kissed or is going to kiss you.

---

**ASSISTANT** No, sentence (4) is grammatically incorrect and may confuse the listener. A better sentence to ask the same question would be, "I wonder who John kissed or if he is going to kiss you."

Model

gpt-4

Temperature

1

Maximum length

256

Stop sequences

Enter sequence and press Tab

# Complex Noun Phrase Island: gpt-3.5-turbo 😞

**USER** (5) John heard the rumor that Mary kissed Tom.

Can I query the identity of Tom in (5) by asking

(6) Who did John hear the rumor that Mary kissed?

**ASSISTANT** Yes, you can query the identity of Tom in (5) by asking (6) "Who did John hear the rumor that Mary kissed?"

**USER** Is (6) a grammatical sentence?

**ASSISTANT** Yes, (6) "Who did John hear the rumor that Mary kissed?" is a grammatically correct sentence. It is an interrogative sentence where "who" is used to inquire about the identity of the person that John heard the rumor about.

Model

gpt-3.5-turbo

Temperature 1



Maximum length 256



Stop sequences

Enter sequence and press Tab

Top P 1



Frequency penalty 0



Presence penalty 0

# Complex Noun Phrase Island: gpt-4 🙄

**USER**

(5) John heard the rumor that Mary kissed Tom.

Can I query the identity of Tom in (5) by asking

(6) Who did John hear the rumor that Mary kissed?

---

**ASSISTANT**

Yes, sentence (6) is a correct way to question the identity of Tom in sentence (5). This sentence is grammatically correct and keeps the meaning of the original sentence intact.

Model

gpt-4

Temperature

1

Maximum length

256

Stop sequences

Enter sequence and press Tab



Why do we know *so much* when we know *so little*?  
Why do LLMs know *so little* when they know *so much*?



## Learnability

“how any agent at all – **human, animal, or machine** – could in principle achieve such a thing as **acquiring a language**”

<https://www.oxfordbibliographies.com/display/document/obo-9780199772810/obo-9780199772810-0077.xml>



- Chomsky: We are born with UG / an innate ability to acquire language.
- LLM seems more powerful than the human brain.
- Can LLMs **acquire human-like linguistic capacity?**
  - (If Chomsky is right about UG...)  
Is UG machine-learnable?

The short answer is

# Ask Cole!





The short answer is **Sure, why not?**

Critics have contended that the machine could produce a black hole that could eat the Earth or something equally catastrophic.

# PLAN FOR TODAY



- LLMs *know grammar*
  - at least, I think so
- *Why* LLMs *can learn grammar*
  - Expressiveness of Transformer
  - Generalization -> Understanding
- LLMs *refute nothing*

LLMs are great at grammar

# LLMS ARE GREAT AT GRAMMAR

In my experience, they are pretty dumb sometimes but grammar never seems to be the issue.

# LLMS ARE GREAT AT GRAMMAR

Model

griffith-santamonica

Prompt

you told me that a blue streak of cherries hit you but why

Top\_p

1

Top\_k

0

Temp

1

max\_tok

128

stop\_tok

token

Resubmit

Response:

did it happen?

A blue streak of cherries hitting you could be a metaphor or a symbolic representation of something. It could mean



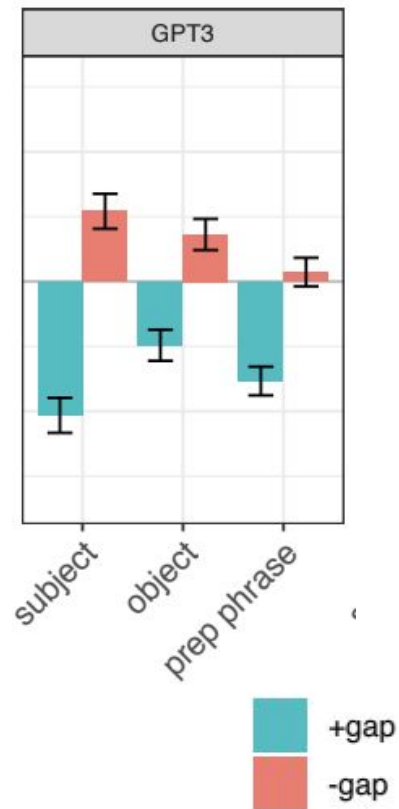
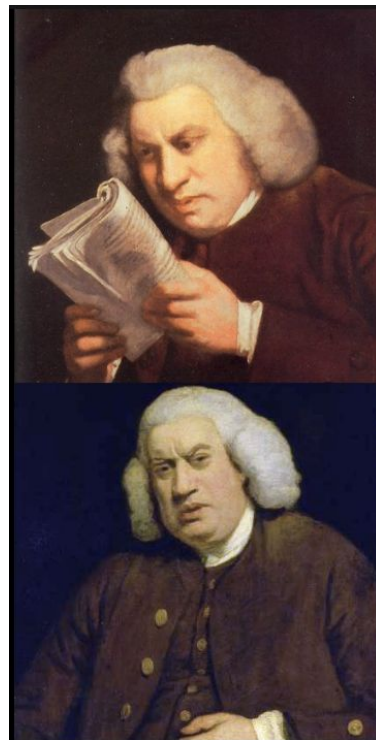
# LLMS ARE GREAT AT GRAMMAR

surprisal:  $-\log(\text{prob}(\text{token}))$

\*I know *who* you met Mary yesterday.

Using Computational Models to Test Syntactic  
Learnability

Ethan Gotlieb Wilcox, Richard Futrell and Roger Levy



# LLMS ARE GREAT AT GRAMMAR

## BERTlarge16

The complex financing plan in the S+L bailout law includes raising \$ 30 billion from debt issued by the newly created RTC .

## ELMo1

The complex financing plan in the S+L bailout law includes raising \$ 30 billion from debt issued by the newly created RTC .

## Proj0

The complex financing plan in the S+L bailout law includes raising \$ 30 billion from debt issued by the newly created RTC .

## A Structural Probe for Finding Syntax in Word Representations

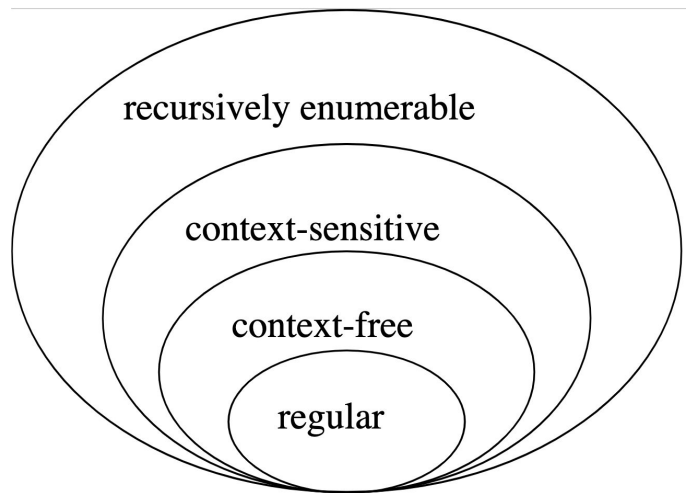
**John Hewitt**  
Stanford University  
johnhew@stanford.edu

**Christopher D. Manning**  
Stanford University  
manning@stanford.edu

But how?

Because they can learn anything!

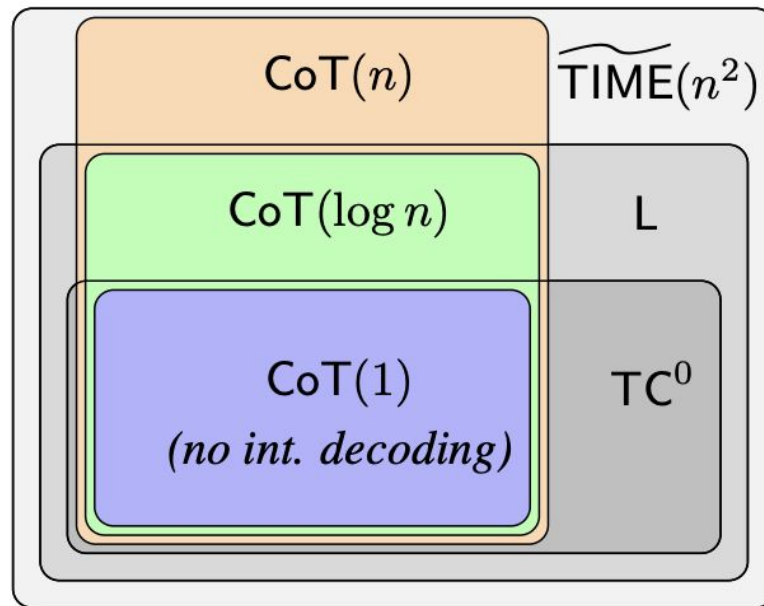
# TRANSFORMERS (WITH COT) ARE EXPRESSIVE!



## THE EXPRESSIVE POWER OF TRANSFORMERS WITH CHAIN OF THOUGHT

William Merrill  
New York University  
willm@nyu.edu

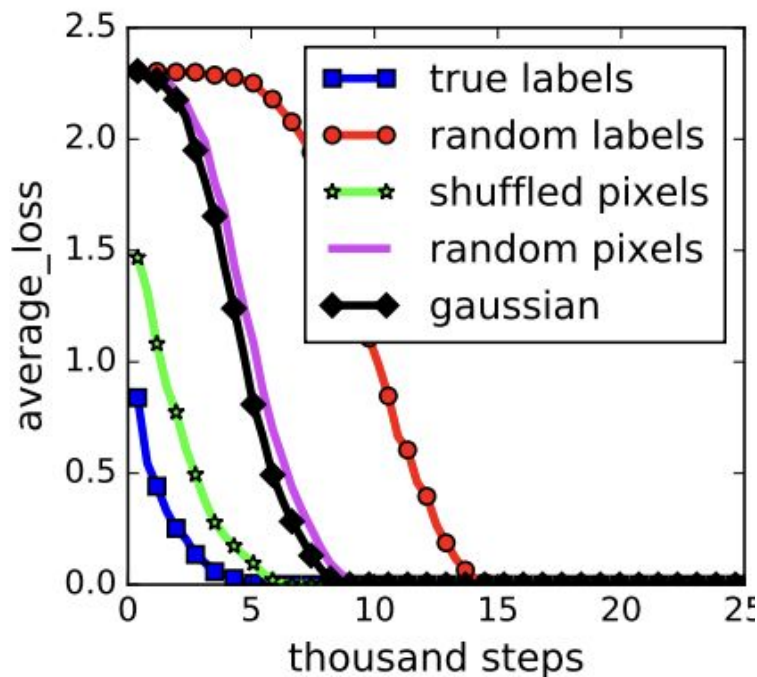
Ashish Sabharwal  
Allen Institute for AI  
ashishs@allenai.org



$$\begin{aligned} \text{TIME}(t(n)) \subseteq \text{CoT}(t(n)) &\subseteq \text{SPACE}(t(n) + \log n) \\ &\subseteq \widetilde{\text{TIME}}(t(n)^2 + n^2) \end{aligned}$$

Sure, they CAN LEARN, but DO they?

# WHAT IF THEY JUST MEMORIZE!



## UNDERSTANDING DEEP LEARNING REQUIRES RE-THINKING GENERALIZATION

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# EVEN IF THEY DO, THEY GENERALIZE

The dream of scale: scaling params + data will result in **understanding** rather than **memorization**

$$L(N, D) = A + \frac{B}{N^{0.34}} + \frac{C}{D^{0.28}}$$

Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, Diego de Las Casas, Lisa Anne Hendricks, Johannes Welbl, Aidan Clark, et al. Training compute-optimal large language models. *arXiv preprint arXiv:2203.15556*, 2022.



# GENERALIZATION => UNDERSTANDING?

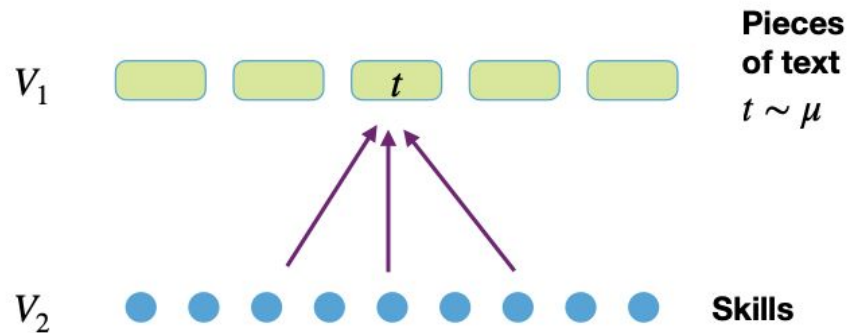
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## A Theory for Emergence of Complex Skills in Language Models

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**Sanjeev Arora**  
Princeton University\*

**Anirudh Goyal**  
Google DeepMind



# OK BUT HOWWWW????

- Arora/Goyal theory shifts the burden from explaining **how they infer** to **how they generalize**
- i.e. why SGD + overparameterization + regularization works so well
- In my opinion, hope lies in showing SGD + overparameterization prefers parsimony (**implicit regularization**)
- Not mechanistic interpretability :(

Does this refute anything?

# NO?

- By seeing tons of data, an expressive model is learning a decidable function. Surprising?
- Humans can do it with way less data; they have better **inductive bias**





war



peace





# war



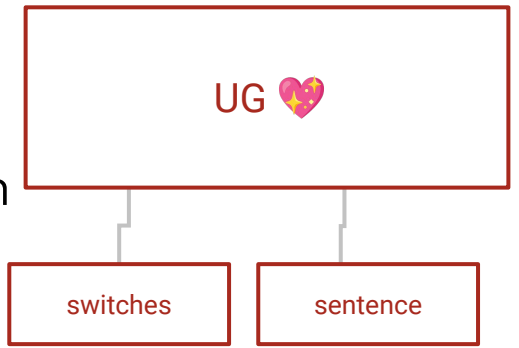
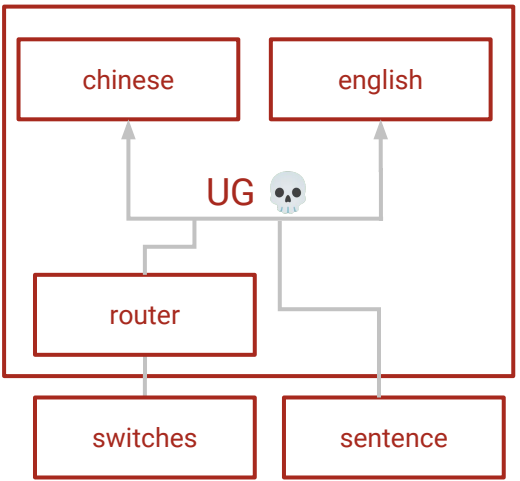
Discussion | Q & A



- **Fulang:** How mechanistically could LLMs detect island constraints? More generally, does LLM have any sense of principles and parameters (or is it just a **look-up table**)?



- **Cole:** But **UG is vacuous...** Also how many principles and parameters have linguists proposed? Is the framework in any sense restrictive?



Takeaway

peace





- The **intricacies of language** make it an **incredibly fascinating subject**.
- To truly grasp its essence, it's crucial to direct our focus towards the **approaches we take** and the **questions we ask**.
- Generative linguists and computer scientists bring distinct perspectives that complement each other, enriching our understanding of language. 🙌



# Exercises

## Lecture 6 Exercises

- How would you imagine giving LLMs access to senses other than sight and sound (i.e. how would you measure and encode touch, smell, taste...)

All you need is an instrument to measure it, and a way to embed it. Smell, taste might be a vectorised output from a mass spectrometer. Touch could be based on pressure or electrical sensors, and embedded positionally.

## Lecture 6 Exercises

- How might you distil signal embeddings such that you reduce ‘noise’ and ensure your model attends to the informative parts of the signal?

Whilst there are some advantages to allowing the LLM to see the whole signal and choose the important parts, we can also use external feature extraction models to transform a signal into a pre-determined feature input (e.g. ASR)

## Lecture 6 Exercises

- Current multimodal models operate mostly on still images/audio. I.e. you provide a 'snapshot' of the modality for context. This sometimes loses information that humans gain from previous context and time-variance.
  - Can you think of an example of this?
  - How you might address this weakness?

e.g. An LLM cannot calculate the speed a person is running at from a still image, and also struggles with time calculations from a video. We could input temporal information manually, or force it to store episodic memory with temporal tagging, but the most reliable way is still to use external tools and have the model act as a tool retriever.

## Lecture 7 Exercises

- What is the rule of -f\*\*king- insertion and how do we train an LLM model to correctly insert -f\*\*king- to any word in English?
- How would you define if an LLM is memorizing a dataset? How few parameters would an llm need to have for you to be confident it wasn't memorizing a dataset?

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