

# CAN CHILD DIRECTED SPEECH HELP US BUILD MORE HUMAN-LIKE LANGUAGE MODELS?

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DATE  
25/02/2025

NAME OF PROJECT  
Polyglot Machines

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ACKNOWLEDGEMENTS AND CONTACTS  
CLCG Lab, Faculty of Arts

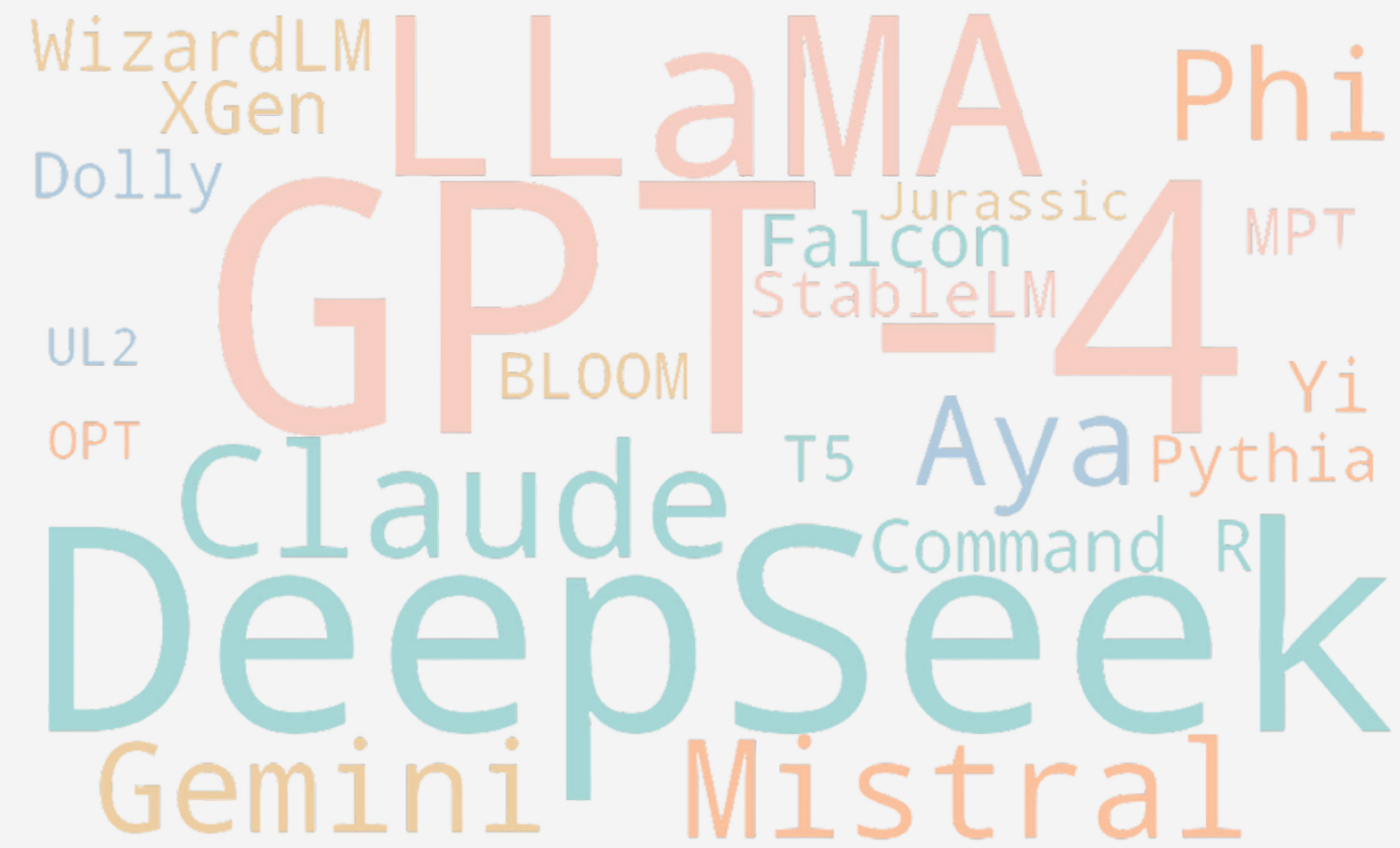
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REFERENCES  
Relevant Literature

A word cloud of various AI models. The most prominent words are GPT-4 (large, orange), LLaMA (large, orange), Claude (medium, teal), and DeepSeek (large, teal). Other visible models include Gemini (orange), Mistral (orange), Phi (orange), WizardLM (orange), XGen (orange), Dolly (blue), UL2 (blue), OPT (orange), Jurassic (orange), Falcon (blue), StableLM (orange), BLOOM (orange), T5 (blue), Aya (blue), Pythia (orange), Command R (orange), and Yi (orange).



scaling as the only viable way to go

A word cloud of various AI models. The most prominent words are 'GPT-4' in large orange letters, 'LLaMA' in large orange letters, and 'DeepSeek' in large teal letters. Other models include 'Claude', 'Gemini', 'Mistral', 'Phi', 'Jurassic', 'Falcon', 'StableLM', 'BLOOM', 'T5', 'Aya', 'Pythia', 'Command R', 'WizardLM', 'XGen', 'Dolly', 'UL2', 'OPT', 'Yi', and 'MPT'.

WizardLM  
XGen  
Dolly  
LLaMA  
Phi  
Jurassic  
Falcon  
StableLM  
MPT  
UL2  
OPT  
BLOOM  
T5  
Aya  
Pythia  
Claude  
Command R  
DeepSeek  
Gemini  
Mistral

scaling as the only viable way to go

extremely high computational and infrastructure costs

A word cloud of AI models. The most prominent words are GPT-4 (large orange), Claude (large teal), and DeepSeek (large teal). Other visible models include LLaMA (large orange), Gemini (orange), Mistral (orange), Phi (orange), Jurassic (orange), Falcon (teal), StableLM (teal), BLOOM (orange), T5 (teal), Aya (teal), Pythia (orange), Command R (teal), WizardLM (orange), XGen (orange), Dolly (blue), UL2 (blue), OPT (orange), and Yi (orange).

scaling as the only viable way to go

extremely high computational and infrastructure costs

near-total industrial monopoly

WizardLM  
XGen  
Dolly  
LLaMA  
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Jurassic  
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lack of transparency and reliability

A word cloud of AI models. The largest and most prominent text is 'GPT-4' in a large, orange-red font. Other models visible include 'LLaMA', 'Phi', 'Claude', 'DeepSeek', 'Gemini', 'Mistral', 'Aya', 'Pythia', 'Command R', 'Jurassic', 'Falcon', 'StableLM', 'MPT', 'Yi', 'BLOOM', 'T5', 'WizardLM', 'XGen', 'Dolly', 'UL2', 'OPT', and 'Claude'. The models are arranged in a dense, overlapping manner, with colors ranging from light blue to orange.

scaling as the only viable way to go

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lack of transparency and reliability

high carbon footprint



WizardLM  
XGen  
Dolly  
LLaMA  
Phi  
GPT-4  
Jurassic  
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MPT  
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scaling as the only viable way to go

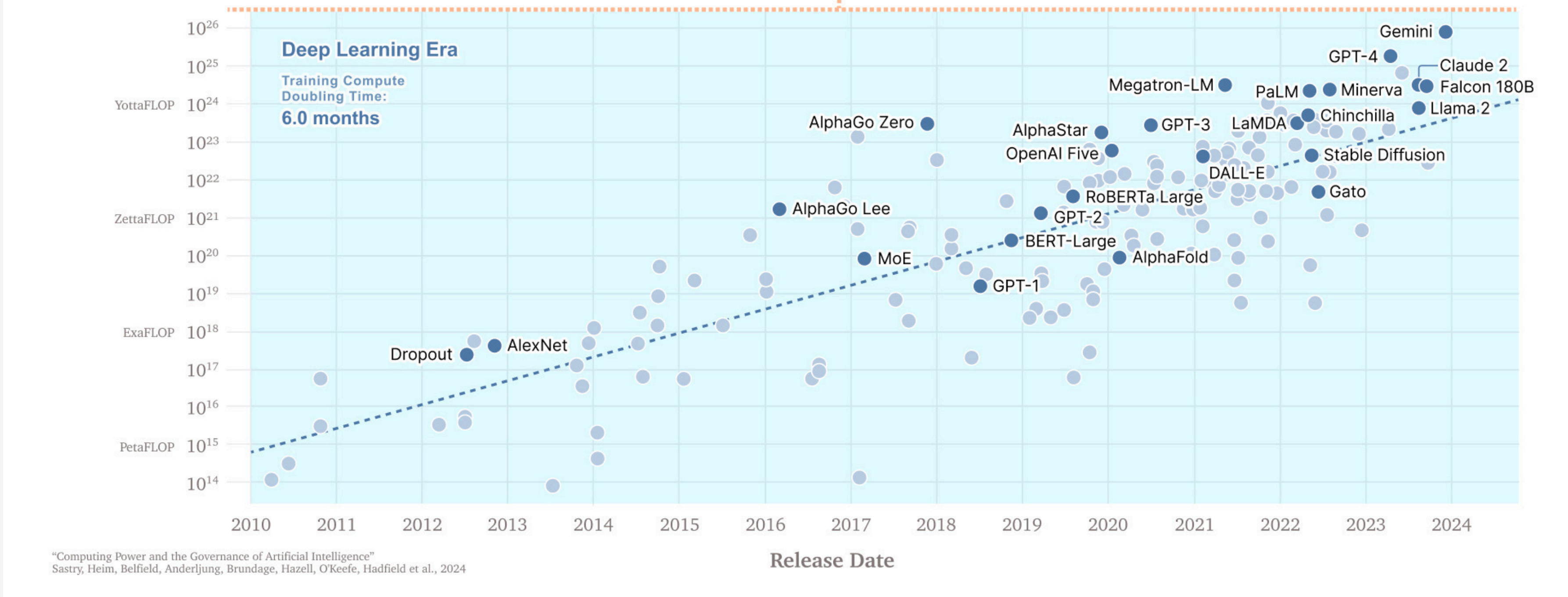
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lack of cognitive plausibility, straying from human-like language learning



Source: Scaling: The State of Play in AI



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Children:



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FOR THEM LANGUAGE TYPOLOGY AND COMPLEXITY DO NOT SLOW DOWN OR OBTACULATE LEARNING

03

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MANY UNDERREPRESENTED LANGUAGES, REPRODUCING AND REINFORCING ALREADY EXISTING INEQUALITIES

	Type	vocab  10k	Example sentence: "I don't want you to play with my lego"
Dutch	fusional	2690	Ik wil niet dat je met mijn lego speel-t I want NEG COMP you with my lego play.PRES
Italian	fusional	2780	Non voglio che giochi con il mio lego NEG want.1SG.PRES COMP play.2G.PRES with DET.PL.M POSS.SG.M lego
Turkish	agglutinative	3970	Lego-m-la oyna-ma-n-ı iste-mi-yor-um lego-1SG.POSS-INS play-VNOUN-2SG.POSS-ACC want-NEG-PRES-1SG

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Great deal of work has to be done to allow for a fair provision of technology for all the languages spoken around the world and to make LMs inclusive with this respect (Blasi et al., 2022).

# CHILD DIRECTED SPEECH / LANGUAGE

*“motherese”*

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CDL holds within itself morphological, syntactic and semantic features that differentiate it from the way adults speak to each other (Rüst et al., 2022; Lester et al., 2022; Onnis & Christiansen, 2008; Stumper et al. 2011; You et al., 2021).

## SALIENT PROPERTIES

simplicity (shorter sentences, reduced vocabulary)

redundancy (repetition of a word in successive sentences, or rephrasing of the same intent)

increasingly growing vocabulary

many vocative expressions to address or call a child directly and gain the child's attention

extensive use of diminutives

They may facilitate identifying basic syntactic structures (Onnis et al., 2008; Lester et al., 2022)

# BABYBERTA

Huebner et al., 2020



Trained a Roberta-base model of reduced size



On a portion of the English CHILDES corpus



Obtaining astonishing results while comparing the model trained on CHILDES to a model trained on



Using a minimal pair benchmark called Zorro

	<b>RoBERTa-base</b>	<b>BabyBERTa</b>
parameters	125M	5M
data size	160GB	0.02GB
words in data	30B	5M
batch size	8K	16
max sequence	512	128
epochs	>40	10
max step	500	260
hardware <sup>1</sup>	1024x V100	1x GTX1080
training time	24hours	2hours
accuracy <sup>2</sup>	81.0	80.5



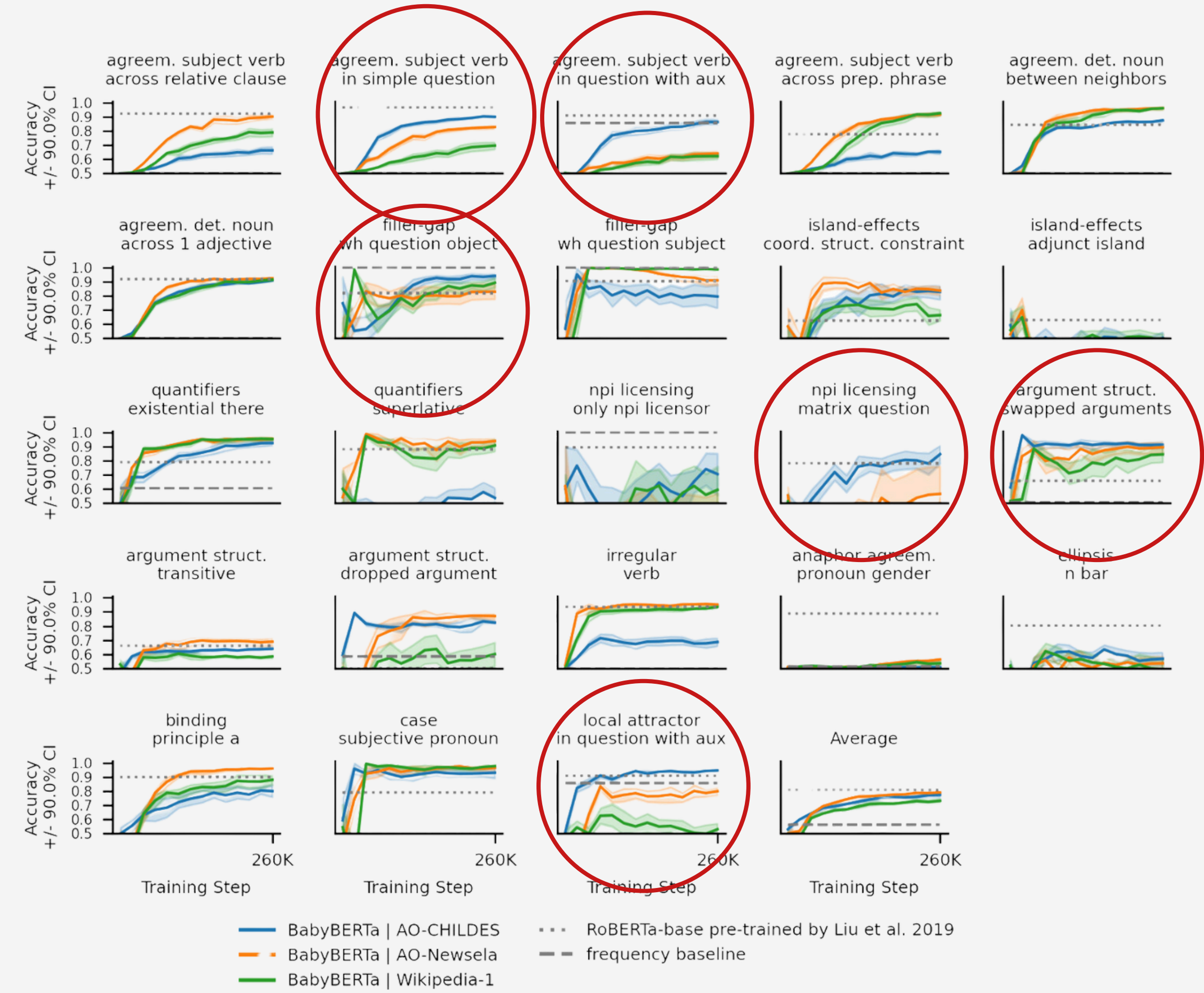
example paradigm: anaphor\_agreement\_pronoun\_gender

should richard tell himself about the cast ?	GRAMMATICAL
should richard tell herself about the cast ?	UNGRAMMATICAL
should she tell herself about the cast ?	GRAMMATICAL
should she tell himself about the cast ?	UNGRAMMATICAL
richard should not tell himself about the cast .	GRAMMATICAL
richard should not tell herself about the cast .	UNGRAMMATICAL
she should not tell herself about the cast .	GRAMMATICAL
she should not tell himself about the cast .	UNGRAMMATICAL

Overall accuracy

Wikipedia	81.0
CHILDES	80.5

But better to have a look at what happens at paradigm level...



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# CURRENT FOCUS

datasets

**CHILDES** in three languages

English - 5M tokens (Huebner et al., 2020)

French - 2M tokens

German - 4M tokens

VS

**WIKIPEDIA** (comparable size)

English - 5M tokens

French - 2M tokens

German - 4M tokens

models

**GPT-2** base model

&

**Roberta** base model (like BabyBERTA)

probing  
benchmark

**CLAMS:** which evaluates agreements in syntactic constructions of different complexities

# CLAMS

## SIMPLE AGREEMENT

the author laughs  
the author laugh  
the author swims  
the author swim

## AGREEMENT IN SUBJECT RELATIVE CLAUSES

the pilots that like the guard laugh  
the pilots that like the guard laughs  
the pilots that like the guard swim  
the pilots that like the guard swims

## AGREEMENT IN OBJECT RELATIVE CLAUSES

the farmers that the skater hate are young  
the farmers that the skater hates are short  
the farmers that the skater hate are short  
the farmers that the skater loves laugh

## AGREEMENT IN PREPOSITIONAL PHRASES

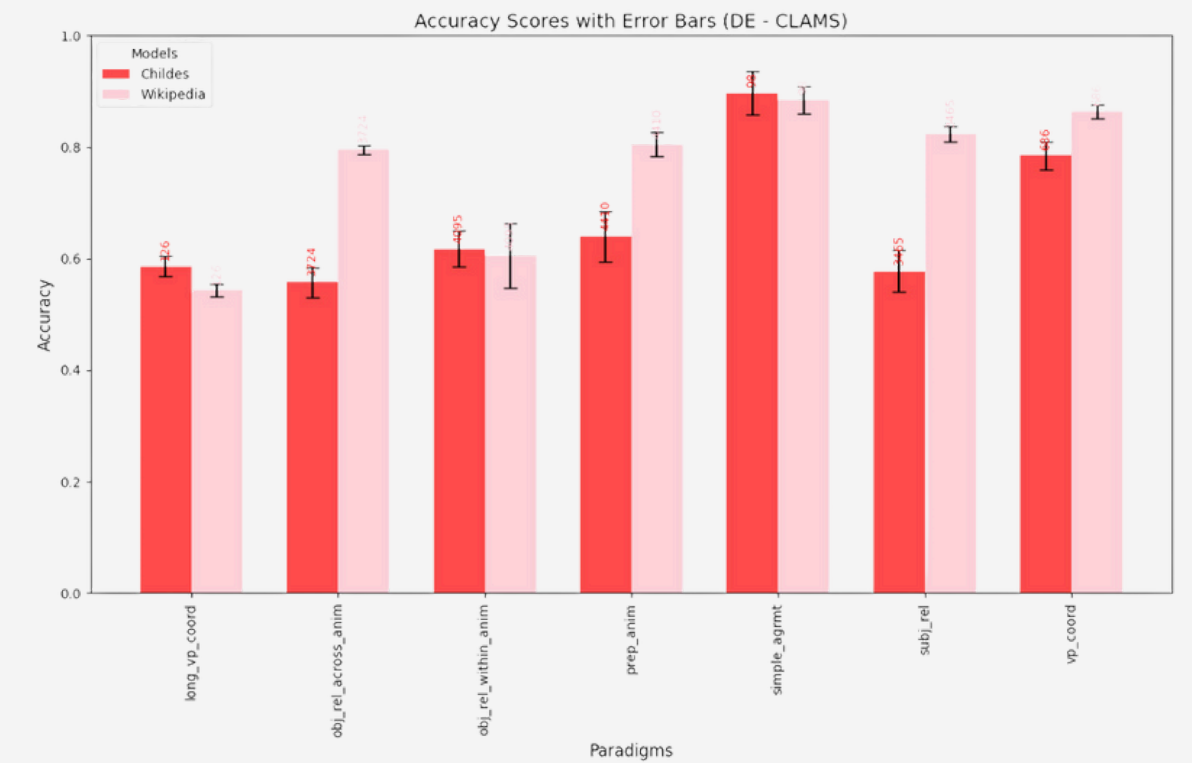
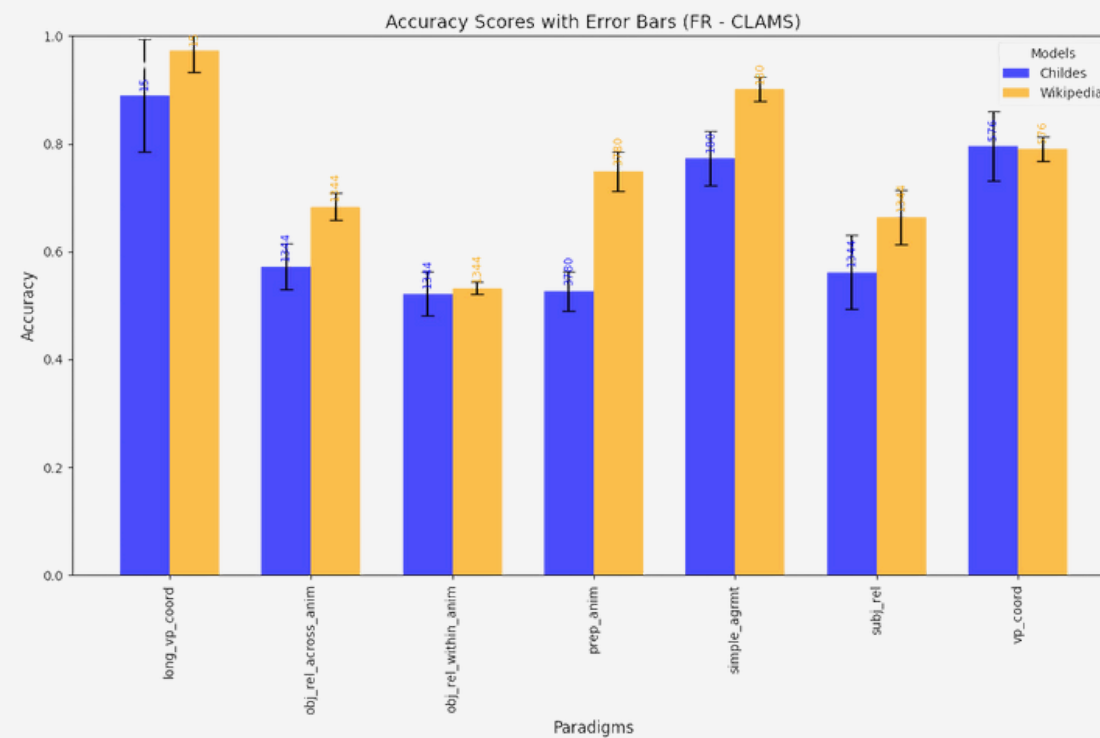
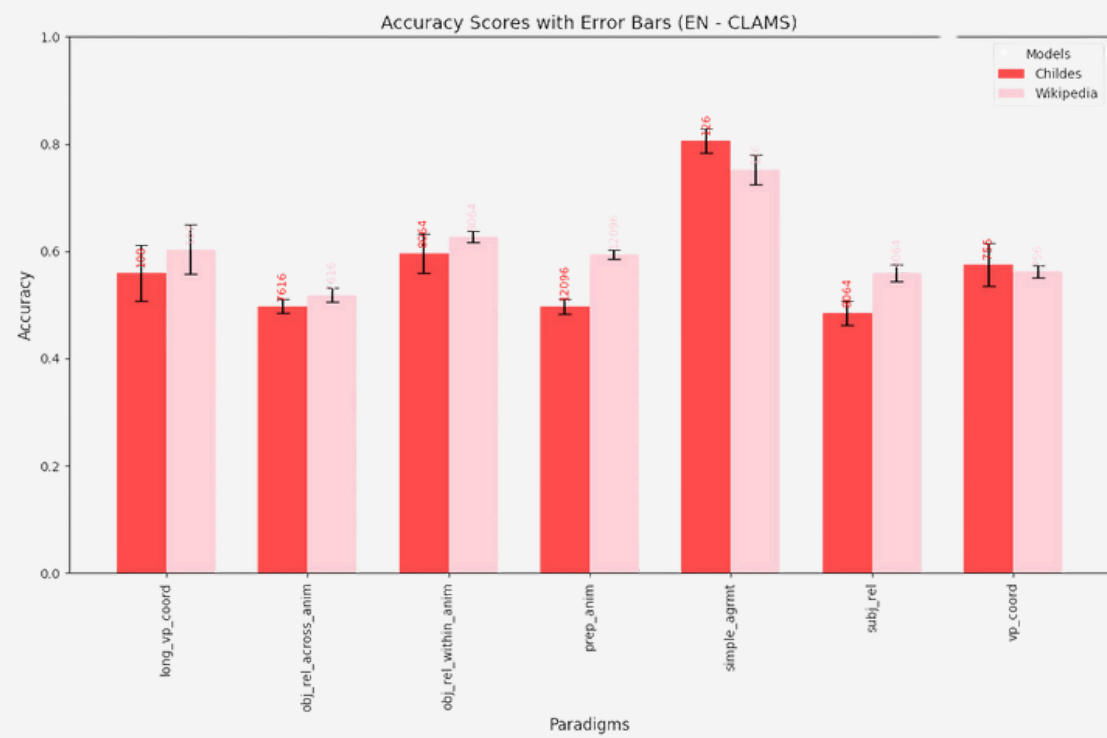
the managers to the side of the dancer swims  
the managers to the side of the dancer smile  
the customers next to the executive are young  
the customers next to the executive is young

## AGREEMENT IN COORDINATES

the senator swims and laughs  
the senator swims and laugh  
the senator swims and smiles  
the senator swims and smile

# ACCURACY SCORES

- The reported results refer to Roberta-base models scores
- Averaged on three seeds



Results from GPT-2 base models are pretty much comparable

CHILDES -trained models outperform WIKIPEDIA-trained ones only on simple agreement for English and German

For French both tests on Agreement in coordinates and Agreement in long coordinates seem to have an advantage when the model is trained on CHILDES

# REGRESSIONS

## Linear Regression and Linear Mixed Effects Models

Modeling the model's log probability scores as a function of training dataset features such as:

- frequency of nsubj (in the two training domains)
- frequency of root (in the two training domains)
- bigram frequency of dependency parsing token-nsubj and token-root (in the two training domains)

minimal_pair	dataset	paradigm	nsubj	verb1	verb2	# subj_log_freq	# verb1_log_freq	# verb2_log_freq
the dreamer assumes, the dreamer assume	wiki	simple_agrmt_new	teachers	write are	write is	4.762173934797756	5.886104031450156	5.886104031450156
the dreamer approves, the dreamer approve	wiki	simple_agrmt_new	teachers	write are	write is	4.762173934797756	5.886104031450156	5.886104031450156
the dreamer insists, the dreamer insist	wiki	simple_agrmt_new	teachers	write are	write is	4.762173934797756	5.886104031450156	5.886104031450156
the dreamer learns, the dreamer learn	wiki	simple_agrmt_new	teachers	write are	write is	4.762173934797756	5.886104031450156	5.886104031450156
the dreamer speaks, the dreamer speak	wiki	simple_agrmt_new	teachers	write are	write is	4.762173934797756	5.886104031450156	5.886104031450156
the dreamer expects, the dreamer expect	wiki	simple_agrmt_new	teachers	write are	write is	4.762173934797756	5.886104031450156	5.886104031450156
the dreamer crashes, the dreamer crash	wiki	simple_agrmt_new	teachers	write are	write is	4.762173934797756	5.886104031450156	5.886104031450156
the dreamer slips, the dreamer slip	wiki	simple_agrmt_new	teachers	write are	write is	4.762173934797756	5.886104031450156	5.886104031450156
the dreamer stands, the dreamer stand	wiki	simple_agrmt_new	teachers	write are	write is	4.762173934797756	5.886104031450156	5.886104031450156
the dreamer knocks, the dreamer knock	wiki	simple_agrmt_new	teachers	write are	write is	4.762173934797756	5.886104031450156	5.886104031450156

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# NEXT STEPS

Linear Regression and Linear Mixed Effects Models

Extensively explore features in regressions

Consider structural variability (making use of dependency parsing tags)

Extend regressions for the three languages

Hopefully get interesting results :)))

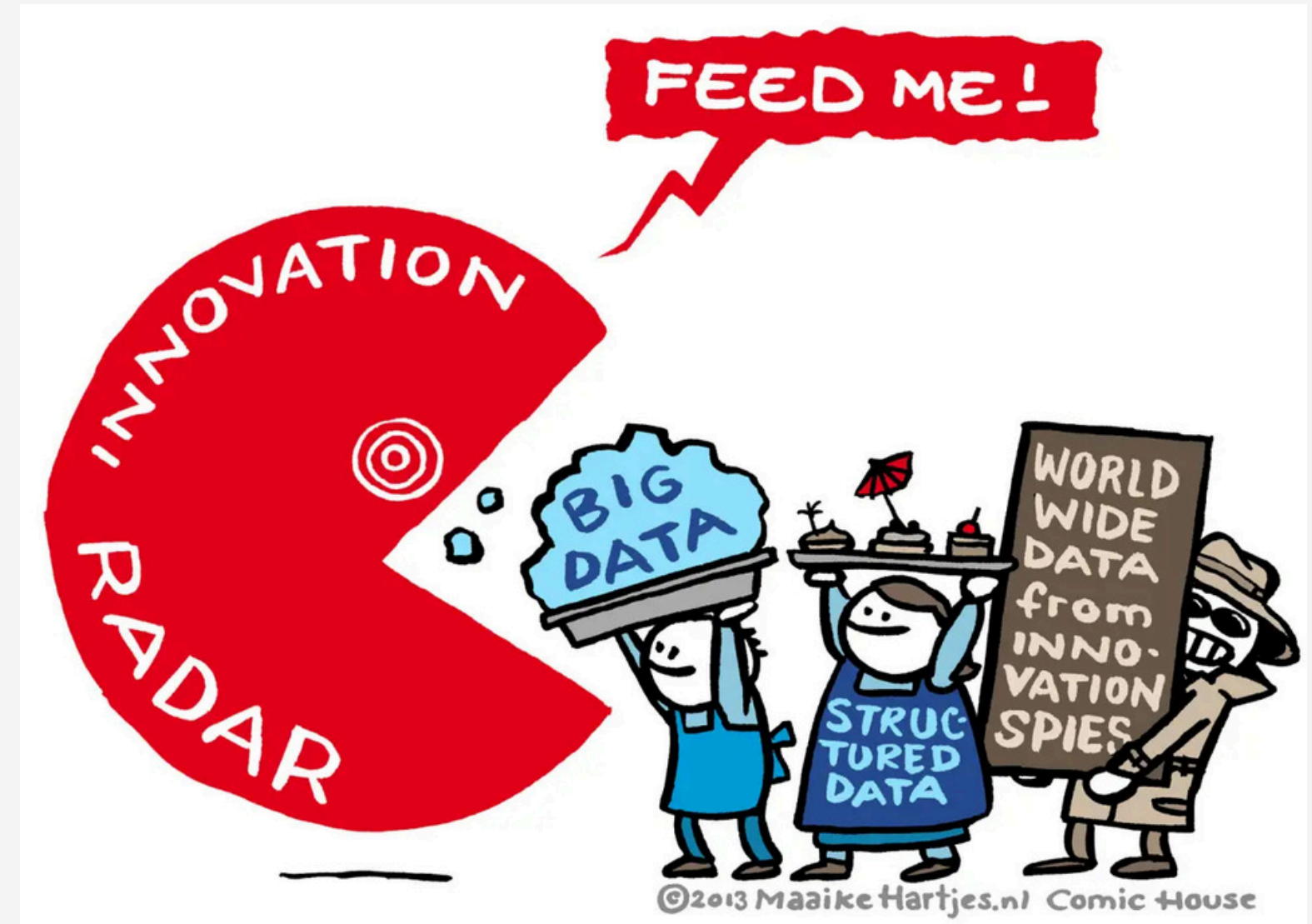
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Thank you ! : - ))

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