# Science of Al and Al for Science

Daniel Khashabi



#### Go Quakers!!





#### REASONING-DRIVEN QUESTION-ANSWERING FOR NATURAL LANGUAGE UNDERSTANDING

Daniel Khashabi

#### A DISSERTATION

in

Computer and Information Sciences

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy 2019

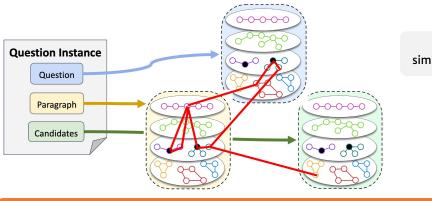
### Inference-time reasoning!!!

AAAI'18

#### **Question Answering as Global Reasoning over Semantic Abstractions**

#### Reasoning With a Meaning Representation

• Support Graph creates potential alignments between various semantic abstractions.



Edges reflect similarity / entailment

QA Reasoning formulated as finding "best" explanation — subgraph connecting the Question to the Answers via the Knowledge

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#### Abstract

e propose a novel method for exploiting the semantic strucre of text to answer multiple-choice questions. The apoach is especially suitable for domains that require reasong over a diverse set of linguistic constructs but have limited aining data. To address these challenges, we present the st system, to the best of our knowledge, that reasons over wide range of semantic abstractions of the text, which are rived using off-the-shelf, general-purpose, pre-trained natal language modules such as semantic role labelers, corefence resolvers, and dependency parsers. Representing mulderive multiple semantic views of the text and perform reasoning over these views to answer a variety of questions.

As an example, consider the following snippet of sports news text and an associated question:

P: Teams are under pressure after PSG purchased Neymar this season. Chelsea purchased Morata. The Spaniard looked like he was set for a move to Old Trafford for the majority of the summer only for Manchester United to sign Romelu Lukaku instead, paving the way for Morata to finally ways to Chelsea for an initial 155m.

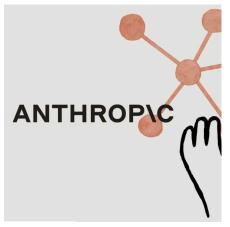
Besides "reasoning", another motivation was "general-purposeness".

We just didn't have the right representation.

#### The progress we dreamed of









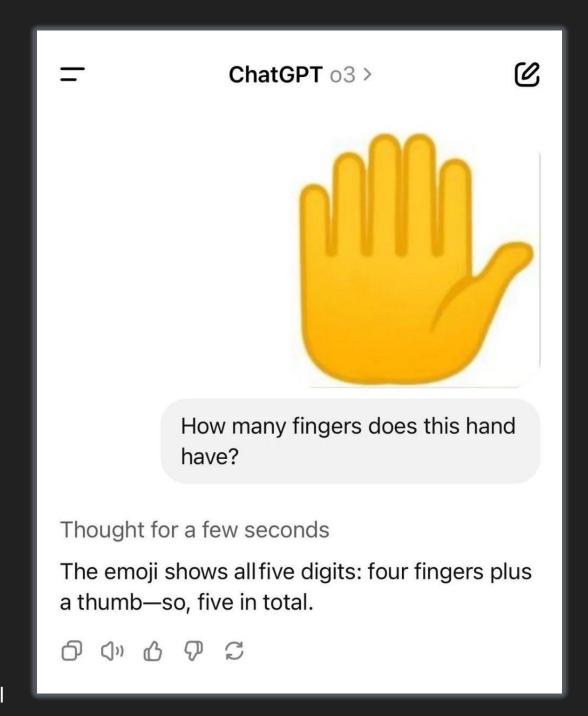
Language models that are remarkably capable at solving many important NLP benchmarks.

### The progress we dreamed of

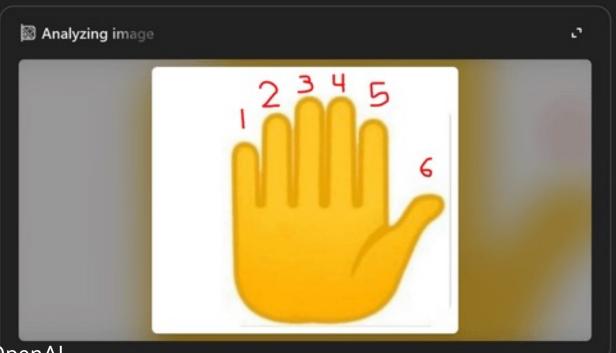


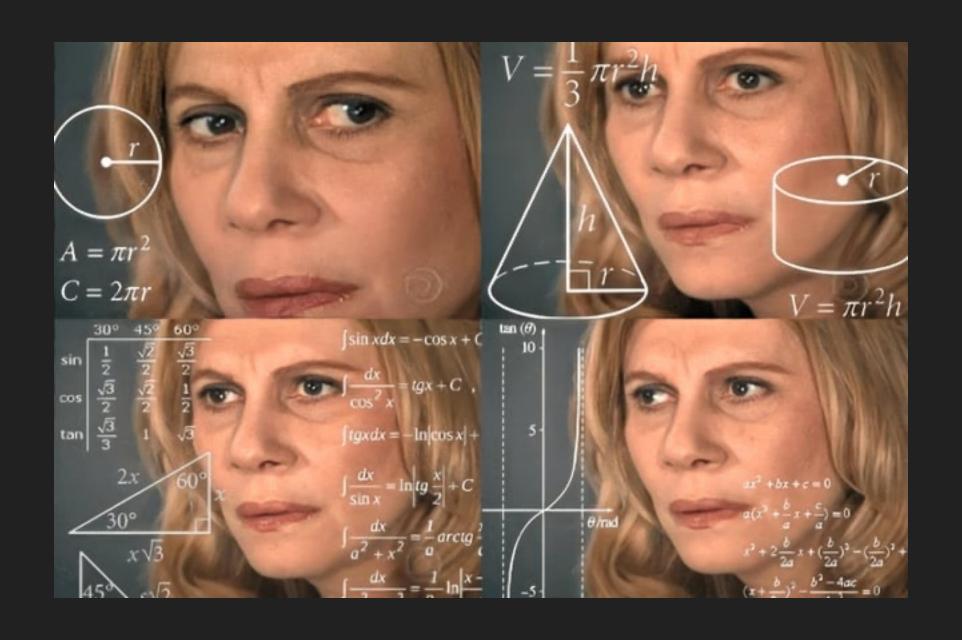
The red-brick Georgian architecture with white trim, slate roofs, and the classic campus walkway setup strongly resembles **Johns Hopkins University**, particularly the Homewood Campus in Baltimore. The buildings and layout are very similar to those in the academic quads there.

### However, LLMs remain brittle ...











Nope. You miscounted the total digits.

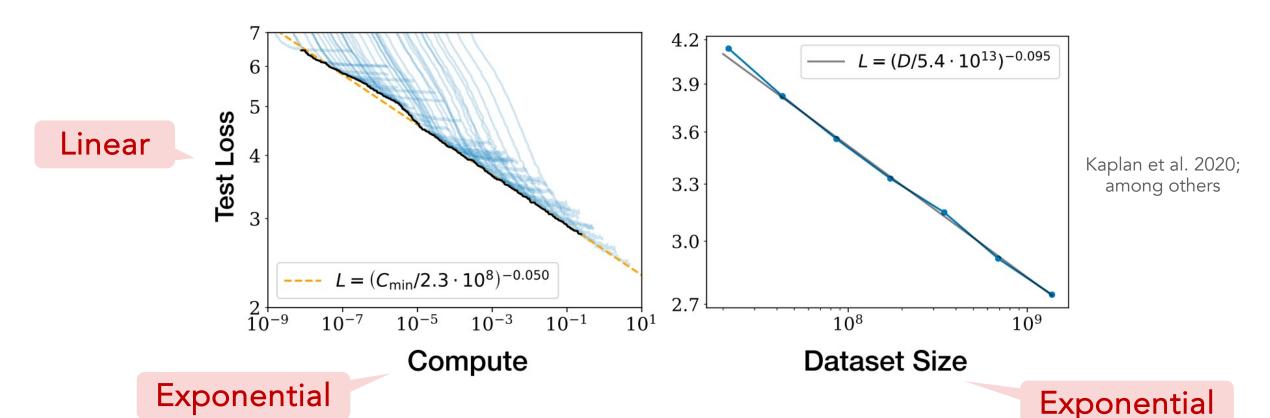
Thought for 1m 15s >

Count the protrusions, not the red numbers:

- Left to right across the top: little finger, ring finger, middle finger, index finger four uprights.
- Off to the right: the thumb, angled outward.

Nothing else sticks out from the palm, so the total remains five digits. Your #5 label got placed above the index finger a second time, which is why it looked like six.

#### Will "scaling" solve LLM brittleness?



Diminishing returns w/ scaling (compute, data, human supervision.)

#### LMs will remain brittle

- We should face this reality.
- It's imperative to understand the scope of their brittleness.

#### Science of Al

- What are the underlying reasons? How can we mitigate them.
- There is so much to "scaling" LLM beyond just scaling.

#### Al for Science

• What are the application frontiers that are near feasible?

### Roadmap



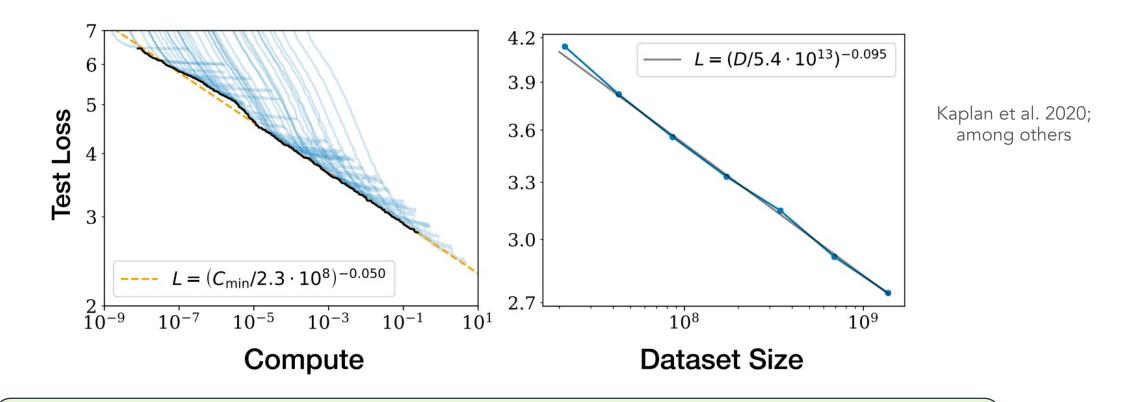
#### Science of Al

Rethinking data.

#### Al for Science

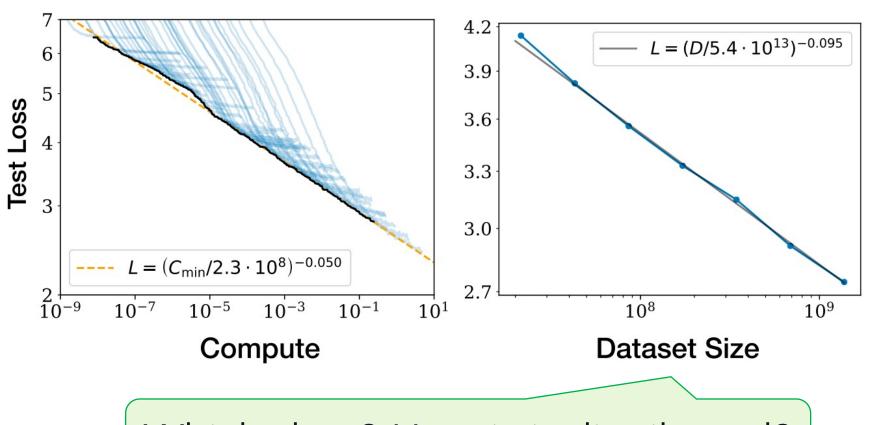
• Few new challenge problems

#### At Data is the "new electricity"



More data (and compute) leads to better models.

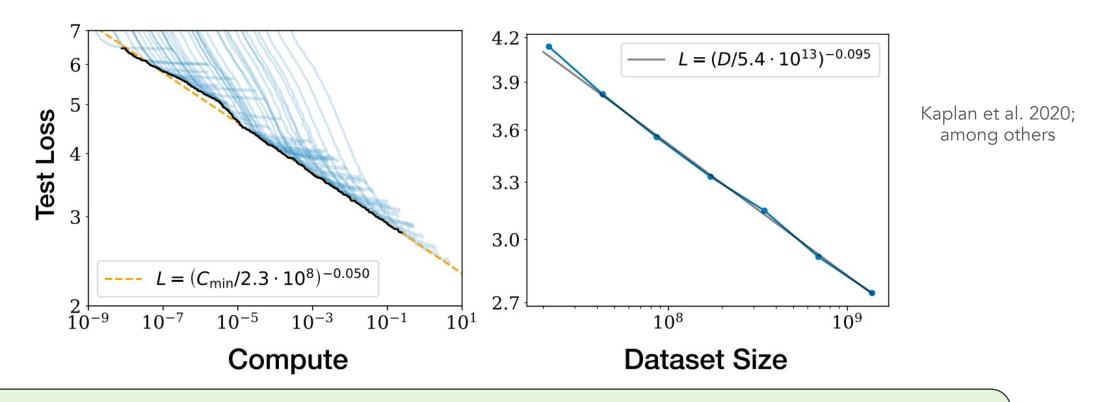
### Limits of scaling "laws"



Kaplan et al. 2020; among others

Which data? How is it distributed?

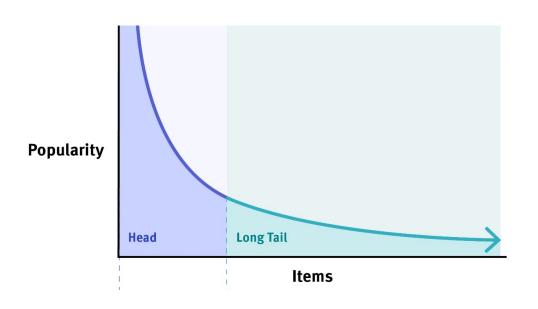
### Limits of scaling "laws"



There are various nuances about data that are not explained any "laws" and remain poorly understood.

### Beyond blackbox laws: knowledge distribution

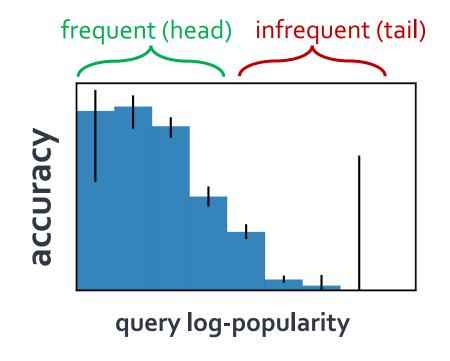
 Knowledge is not uniformly distributed.



### Beyond blackbox laws: knowledge distribution

 Knowledge is not uniformly distributed.

Factual accuracy of LLMs is positively correlated with "popularity" of the input prompts.



### Beyond blackbox laws: Knowledge Cutoffs



My knowledge cutoff date is September 2023. Anything that has occurred or been released after that date may not be included in my responses unless I use real-time browsing. Let me know if you'd like me to look up more recent information.

My knowledge was last updated in April 2024. When discussing events or developments, I approach it as a well-informed individual from April 2024 would if speaking to someone in October 2024. If you have questions about more recent events, I'll do my best to help based on trends and information available up to my knowledge cutoff, but I may not be aware of specific developments that occurred after April 2024.

#### **Training Data**

**Overview** Llama 3 was pretrained on over 15 trillion tokens of data from publicly available sources. The fine-tuning data includes publicly available instruction datasets, as well as over 10M human-annotated examples. Neither the pretraining nor the fine-tuning datasets include Meta user data.

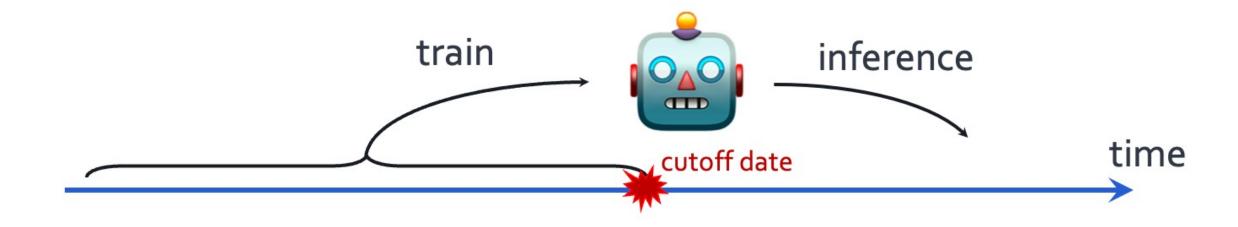
**Data Freshness** The pretraining data has a cutoff of March 2023 for the 8B and December 2023 for the 70B models respectively.

**Overview:** Llama 3.1 was pretrained on ~15 trillion tokens of data from publicly available sources. The fine-tuning data includes publicly available instruction datasets, as well as over 25M synthetically generated examples.

Data Freshness: The pretraining data has a cutoff of December 2023.

### Temporal misalignment: LLMs stale over time

LLM quality degrade after their cut off date.



#### How reliable is LLM knowledge before the cutoff?

#### What users want:

• Always use the latest version of facts, if there is any update.



2022 **MIRS** 



Form 1099-K is issued for transactions only if the aggregate amount of these transactions exceeded \$20,000

2024 MIRS

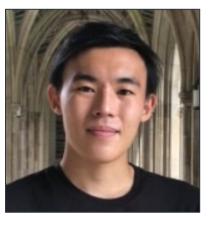


Now a single transaction exceeding \$5000 can require the third party platform to issue a 1099-K.

#### **Dated Data:**

#### Tracing Knowledge Cutoffs in Large Language Models

Jeffrey Cheng, Marc Marone, Orion Weller, Dawn Lawrie, Daniel Khashabi, Benjamin Van Durme



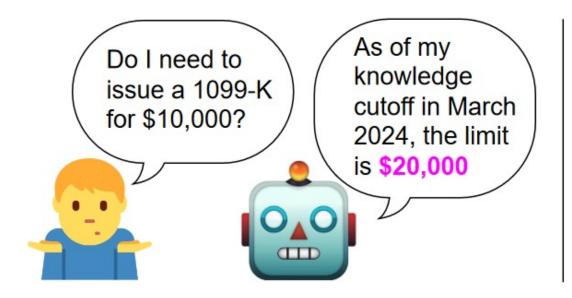






#### LLM reliability before the cutoff

How should we quantify this?



2022 **MIRS** 

Form 1099-K is issued for transactions only if the aggregate amount of these transactions exceeded \$20,000

2024 **MIRS** 

Now a single transaction exceeding \$5000 can require the third party platform to issue a 1099-K.

#### How do we measure knowledge over time?

- WIKISPAN:
  - Collect 5000 most edited topics
  - Scrape monthly versions from April 2016 to April 2023





with the advice and consent of the Senate. The president is further

adjourn either or both houses of Congress under extraordinar

president and the federal government has grown substantia.

empowered to grant federal pardons and reprieves, and to convene and

circumstances.[12] The president is largely responsible for dictating the

legislative agenda of the party to which the president is enrolled. The

States, [13] Since the founding of the United States, the power of the

sident also directs the foreign and domestic policy of the United



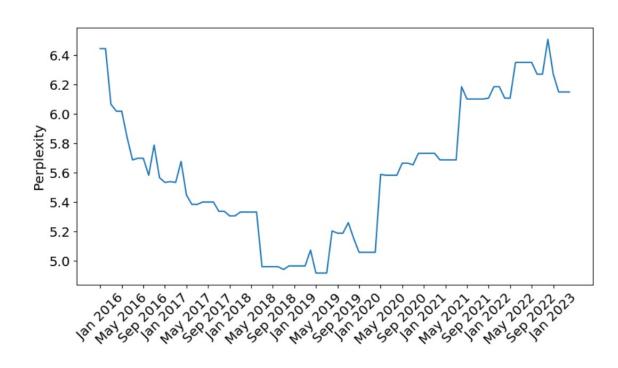






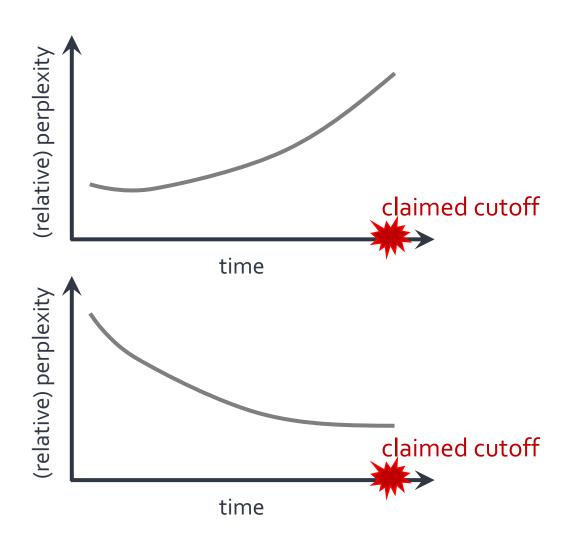
#### Extract PPL over time with WIKISPAN

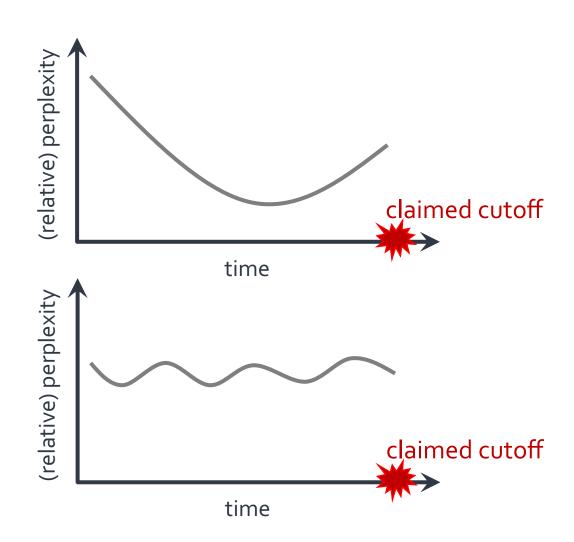
- WIKISPAN documents: version of Wikipedia topic t at time m
- Measure perplexity of first
   512 tokens of each document,
   across all topics and months
- Perform 0-1 normalization over entire time-span



Perplexity of the Wikipedia document "Liverpool" under Pythia-7b. Each point is the perplexity of the document at that time.

### Expectation: which trend would you expect?



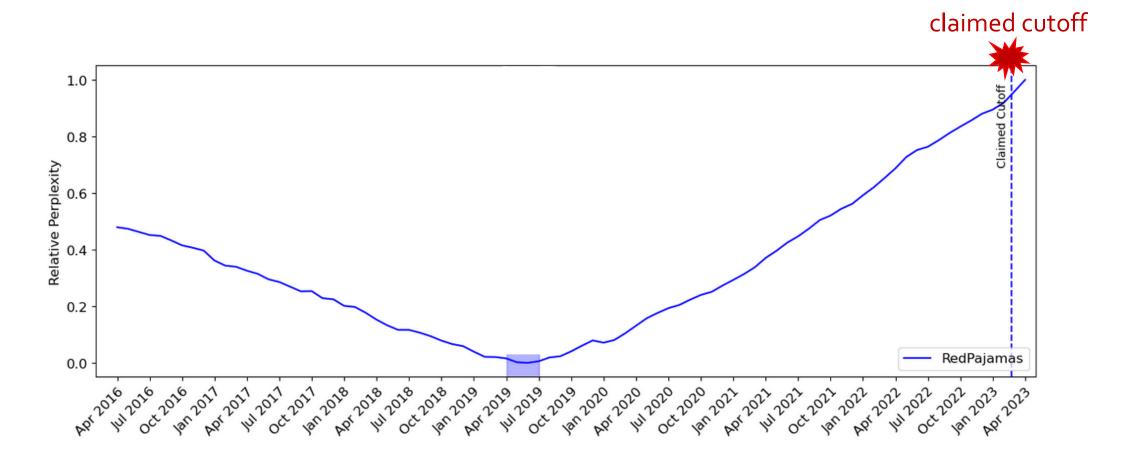


#### PPL of RedPejamas over time

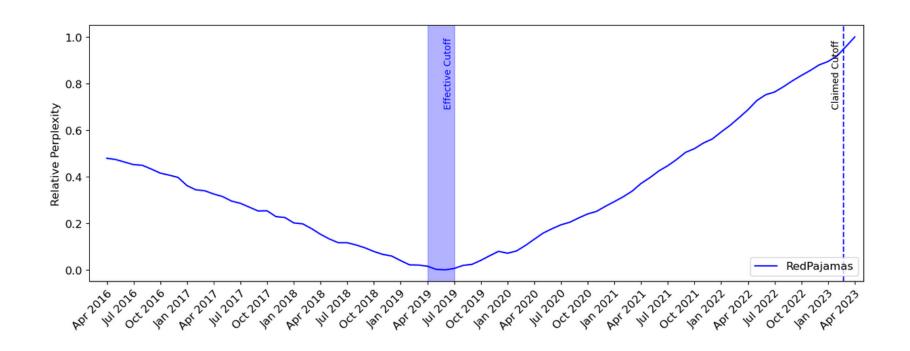
#### RedPajamas (Together Computer)

"We use the Wikipedia dataset available on Huggingface, which is based on the Wikipedia dump from 2023-03-20 and contains text in 20 different languages. The dataset comes in preprocessed format, so that hyperlinks, comments and other formatting boilerplate has been removed."

#### PPL of RedPejamas over time

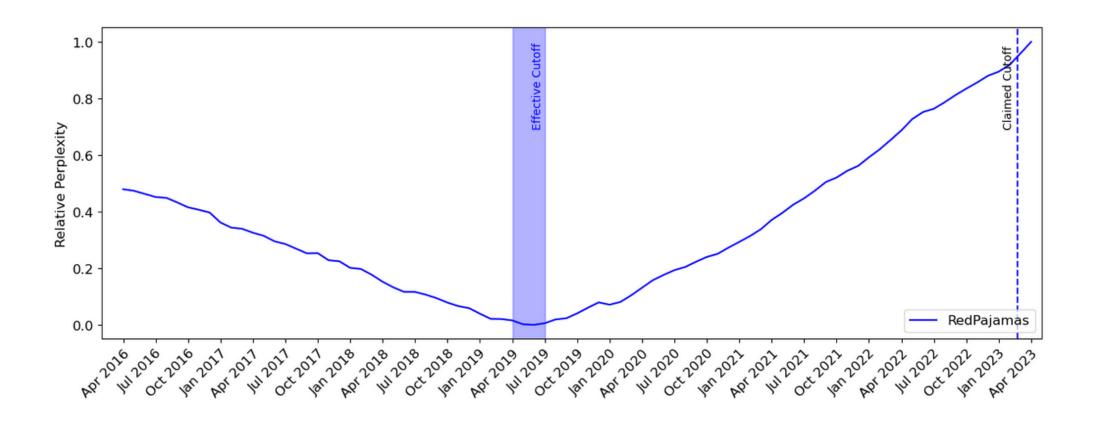


#### "Effective Cutoff"

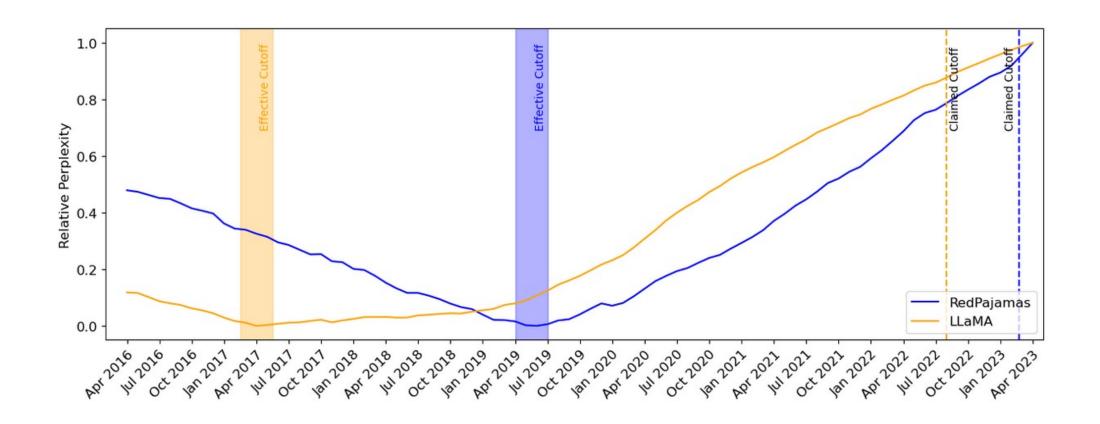


The <u>effective cutoff</u> of an LLM with respect to a resource is the date that matches the LLM's best knowledge of that resource.

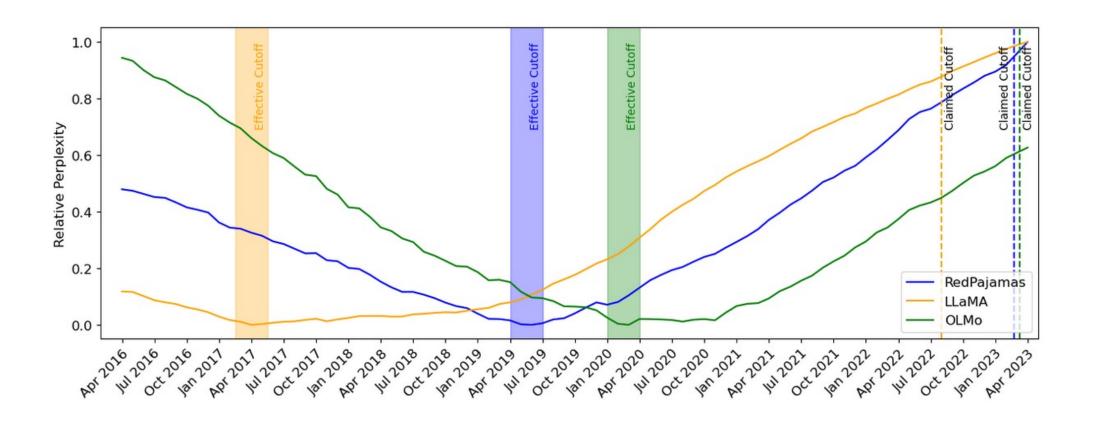
#### "Effective Cutoff" in other models



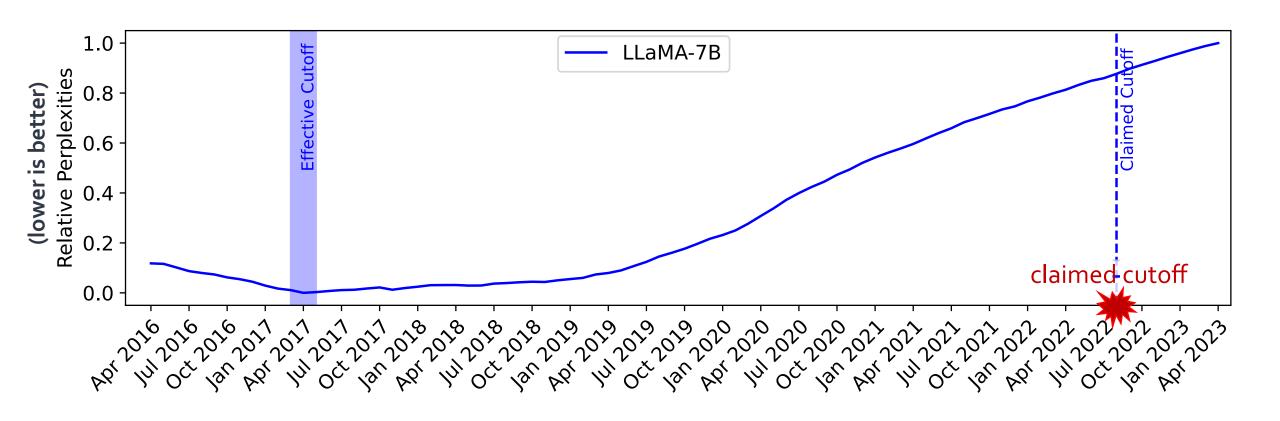
#### "Effective Cutoff" in other models



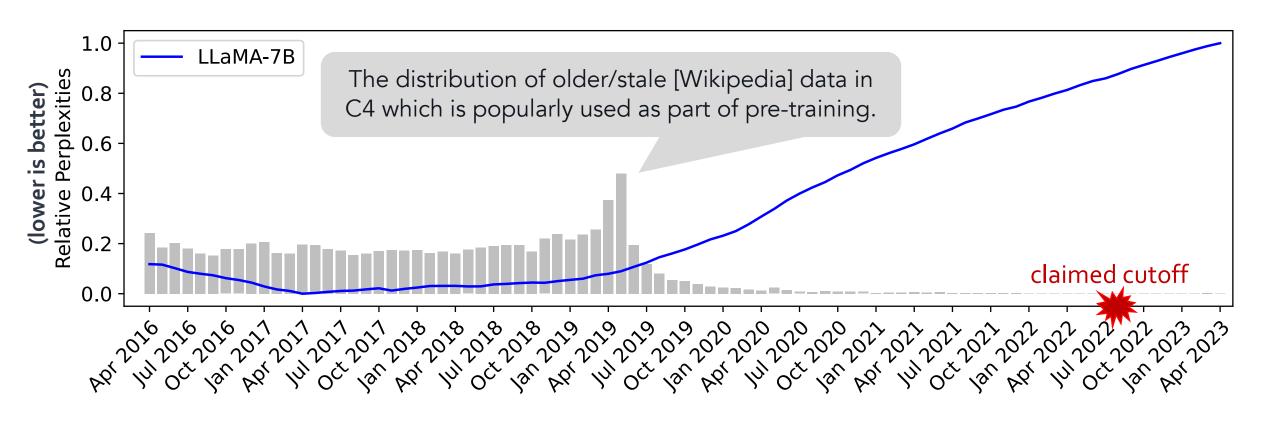
#### "Effective Cutoff" in other models



## Why such discrepancies exist between effective vs. reported cutoffs?



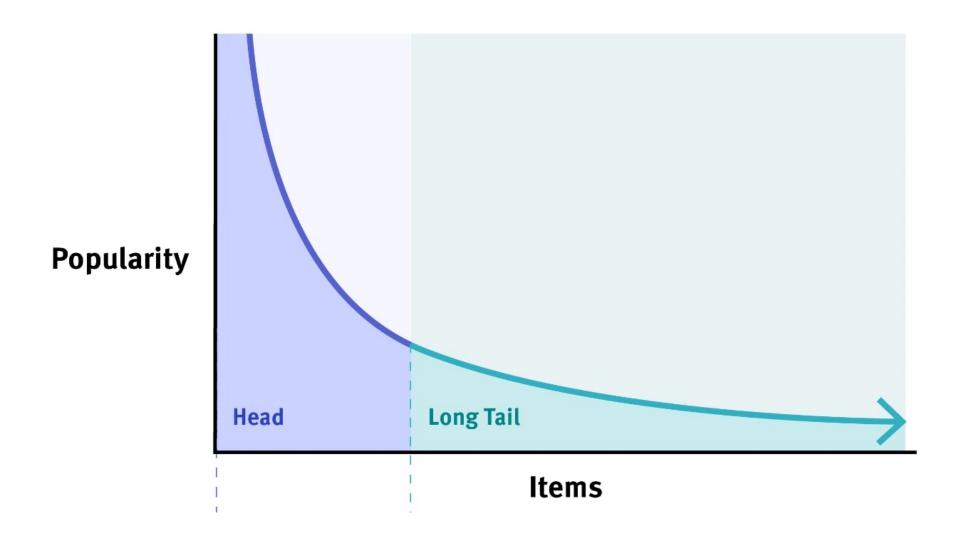
#### Pre-training data contain lots of old/stale data



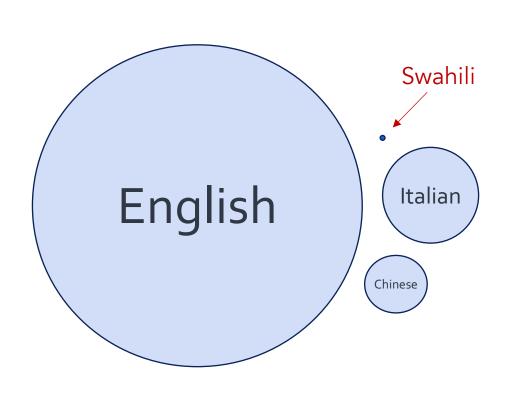
### Summary thus far

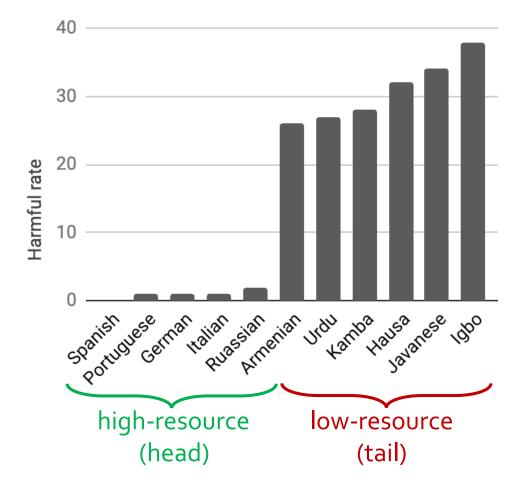
- Effective cutoffs of recent LLMs are years earlier than reported cutoff
  - CommonCrawl dumps include older versions of resources
  - Not explained by scaling "laws"!
- There are exceptions:
  - Effective cutoffs of Pile-derived models matches their reported cutoff
  - Small amount of CommonCrawl used (< 25% of one CC dump)</li>
- Open question: what is the implication for applications?

# Long-tail of problems: There are many infrequent concepts/problems



### Example: The long-tail of languages



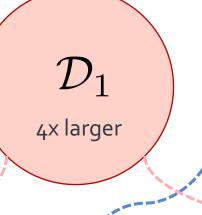


Tokens of pretraining data by language in mC4 (Xue+ 2024)

The Language Barrier: Dissecting Safety Challenges of LLMs in Multilingual Context. (Shen et al. *ACL* 2024)

# How should we [pre-]train on imbalanced data?

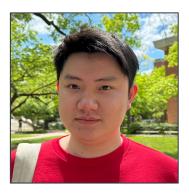
Scalarization
(sample uniformly;
upweight small domain)



Sampling
(oversample small domain;
average uniformly)

# Upsample or Upweight? Balanced Training on Heavily Imbalanced Datasets

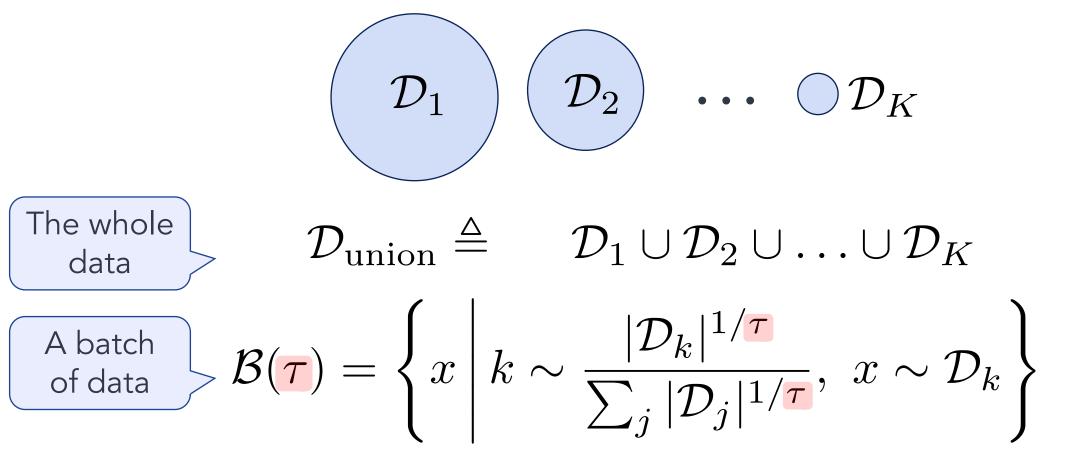
Tianjian Li, Haoran Xu, Weiting Tan, Kenton Murray and Daniel Khashabi.



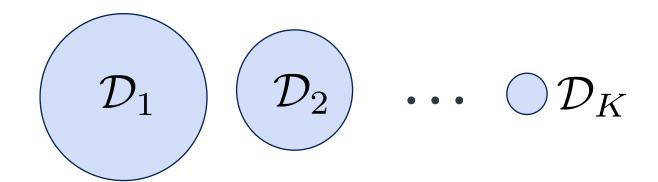
To appear in NAACL '25 (next week!!)

## Training on a collection of "domains"

ullet Consider training a model on a collection K domains:



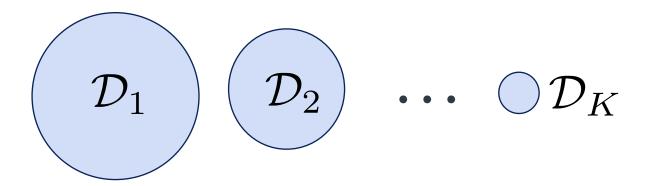
### Training on a collection of "domains"



$$\mathcal{B}(\tau) = \left\{ x \middle| k \sim \frac{|\mathcal{D}_k|^{1/\tau}}{\sum_j |\mathcal{D}_j|^{1/\tau}}, \ x \sim \mathcal{D}_k \right\}$$

- au=1 uniform sampling from the whole data.
- au > 1 oversamples smaller domains.
- $au o \infty$  samples equal number from each domain.

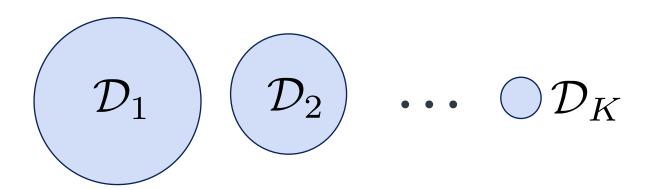
### Temperature Sampling (TS)



$$abla_{TS}( au) := \sum_{x \in \mathcal{B}( au)} \left. \nabla \ell \right|_x$$

With au>1 oversample infrequent domains, effectively duplicating the data multiple times.

### Scalarization (S)

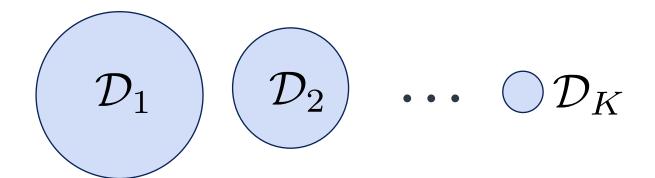


$$\nabla_{S}(\mathbf{w}) := \sum_{x \in \mathcal{B}(\tau=1)} w_{f(x)} \nabla \ell \Big|_{x} \qquad f : \mathcal{X} \to [K]$$

Uniformly sampled from the whole data Assigned a higher weight to the smaller domains

maps each data to its domain

### Scalarization (S) vs Temperature Sampling (TS)



$$\nabla_{S}(\mathbf{w}) := \sum_{x \in \mathcal{B}(\tau=1)} w_{f(x)} \nabla \ell \Big|_{x} \qquad \nabla_{TS}(\tau) := \sum_{x \in \mathcal{B}(\tau)} \nabla \ell \Big|_{x}$$

Which one would would you use?

### "Temperature Sampling" often assumed to be equivalent to "Scalarization"

In our work, we follow convention and implement scalarization via proportional sampling, where data from task i is sampled with probability equal to  $w_i$ . In this of the expected loss is equal to the loss from scalarization:

the expected loss is equal to the alarization: 
$$\mathcal{L}(\theta) = \mathbb{E}_{\boldsymbol{x}}\left[\ell(\boldsymbol{x};\theta)\right] = \sum_{i=1}^{K} \mathbb{P}(\text{task}, \boldsymbol{x}; \boldsymbol{\theta}) = \sum_{i=1}^{K} \boldsymbol{w}_{i} \mathcal{L}_{i}(\boldsymbol{\theta}). \tag{2}$$
Matters in the Presence of Data for Multilingual Learning (Choi et al., NeurlPS 2024)

calarization. For the NMT literature's convention, we implement scalarization via the part of observations in the batch corresponding to task of the sampling.

Order Matters in the Presence of Data or Multilingual Learning (Choi et al., NeurIPS 2024)

frontier of scalarization. Fo ME NMT literature's convention, we implement scalarization via proportional sampling. Here, average number of observations in the batch corresponding to task i

Do Current Multi-Task Optimization Methods Even Help? (Xin et al., NeurIPS 2022)

### Scalarization (S) vs Temperature Sampling (TS)

• Both approaches are good, if you have very large batch sizes.

Theory (informal): gradients estimation based on S and TS are both unbiased estimators (of gradient on full dataset).

• However, their variances are different.

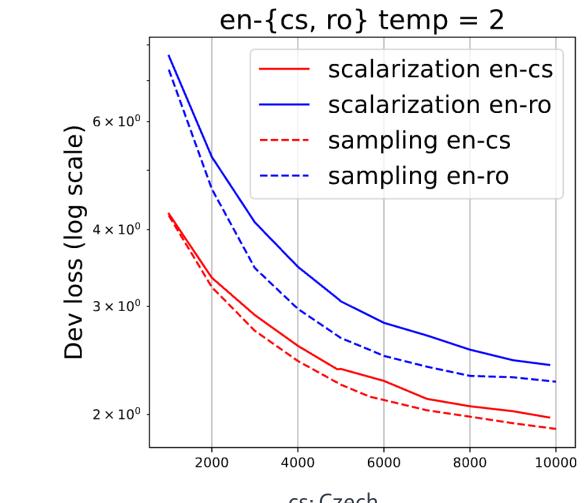
Theory (informal): Gradients estimates of S have lower variance than TS. Their gap increases monotonically with higher temperature.

# TS vs S: How do they affect my optimization?

• It is well-known that variance-reduction accelerates the convergences of SGD (Sutskever et al., 2013; Kingma and Ba, 2015)

• Temperature Sampling reduces gradient variance, therefore it should converge faster??

# TS vs S: Convergence speed

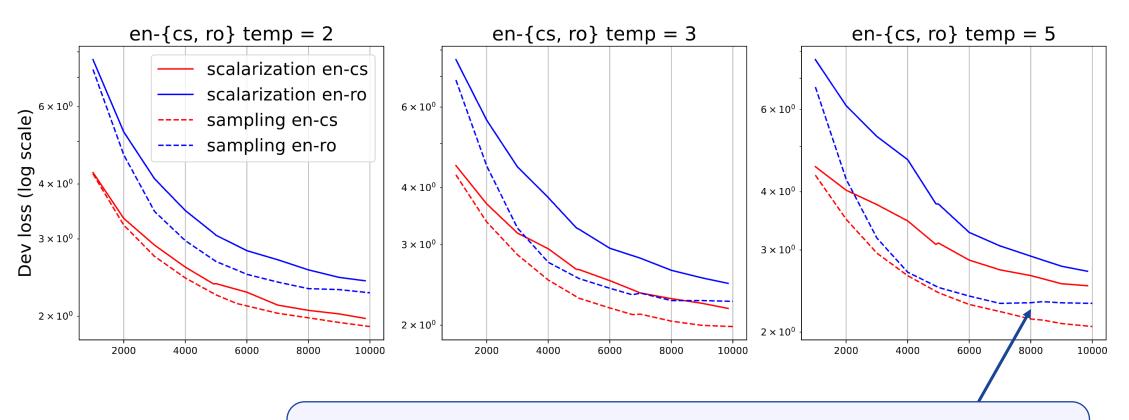


 We train an MT model for pair of high and low-resource languages.

Temperature Sampling (dashed) converges faster than Scalarization (solid.

cs: Czech ro: Romanian

## TS vs S: Convergence speed



Increasing temperature (2 to 5) makes the convergence even faster, but easy to overfit (to small domains).

### ☼ CoolDown ※: Adapting sampling temperature

- When using temperature sampling, we need balance between:
  - High-temperature (faster convergence)
  - Low-temperature (avoid overfitting)

### CoolDown \*\*

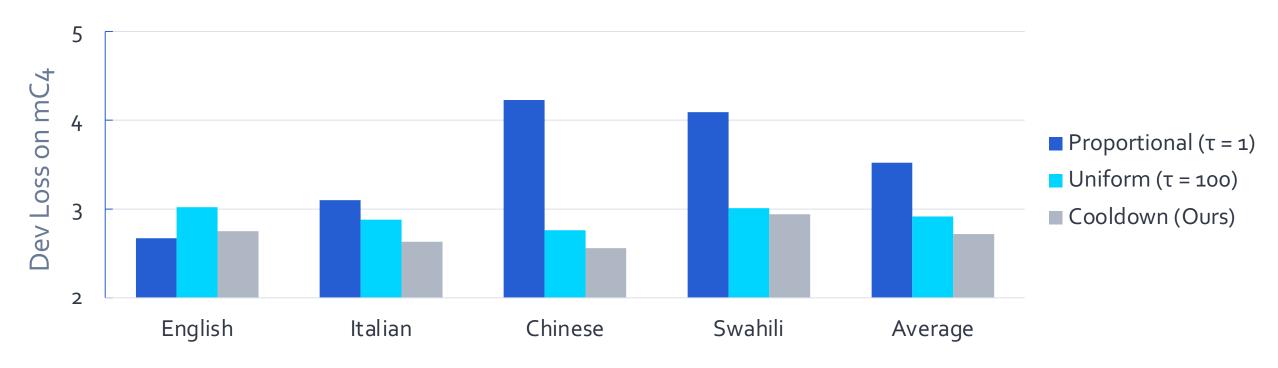
Train with Temperature Sampling

- Start with a high-temperature
- During training reduce temp

Over-sample low-resource domains

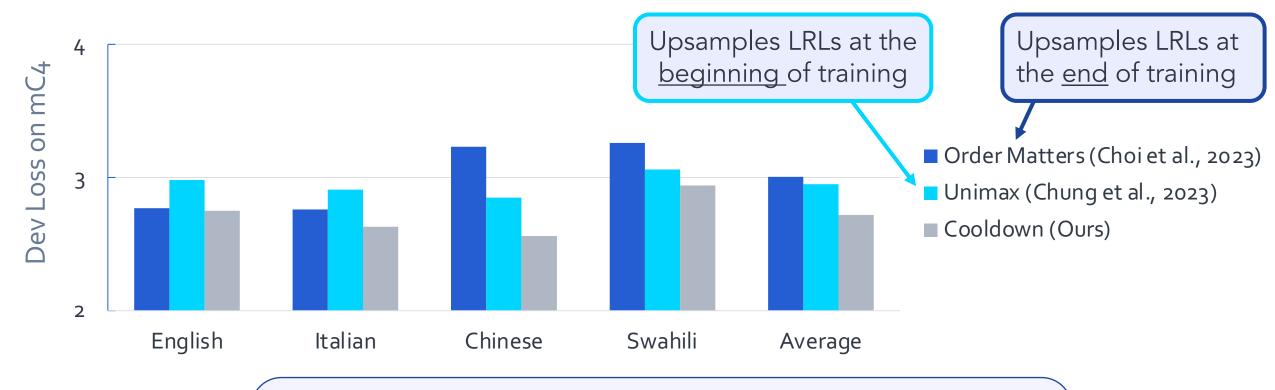
Remove the oversampling over time

## Multilingual Language Modeling



COOLDOWN outperforms fixed-temperature sampling.

### Multilingual Language Modeling



COOLDOWN outperforms existing work that dynamically adjusts the sampling temperature!

### Summary

- Common approaches for training on imbalanced data:
  - Sampling vs Scalarization
- Despite common perception, these two are not equivalent.
- CoolDown \*
  - A suggested recipe for imbalanced [pre-]training
- Open question: Do these actually scale?

### Data ←→ LLM behavior

• These (data staleness, imbalance, etc.) are not captured by scaling laws.

• Our understanding of data and its impact on behavior remains quite primitive.

• The heavy focus on "scaling laws" may be have been counterproductive, as it disincentivizing a deeper understanding of data.

# Today



#### Science of Al

• Rethinking data.

#### Al for Science

• Few new challenge problems

# Today



#### Science of Al

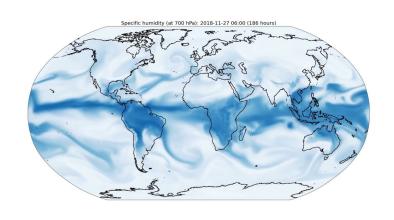
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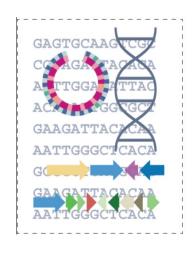
#### Al for Science

• Few new challenge problems

### Al for Science





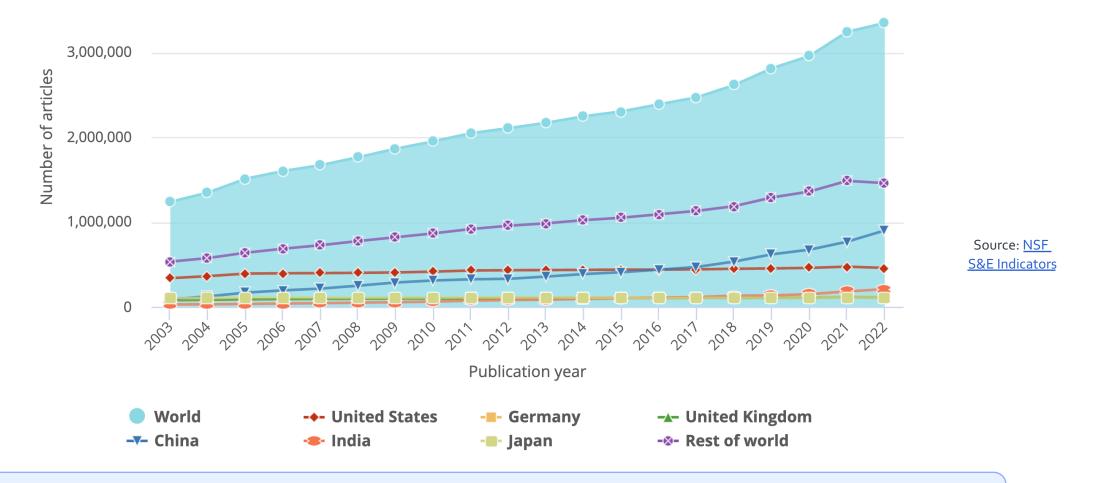


**Protein Folding** (e.g., AlphaFold, 2022)

Climate Modeling (e.g., AlphaFold, 2022)

**Drug Discovery** (e.g., Insilico Medicine)

### "Digesting" science is getting difficult



It's near impossible to keep track of science, even within its sub-fields.

### Data ↔ LLM behavior ↔ Science discovery

#### Cutoff dates and data staleness:

 Science keeps evolving. How do you know that your model retains the latest version of findings?

#### Data imbalance:

• Few findings/papers are overly repeated. A lot of science is less repeated (if any).

### Science queries: Information seeking vs Aggregative

Information seeking queries:



Query: What was GPT3's approach to alignment?

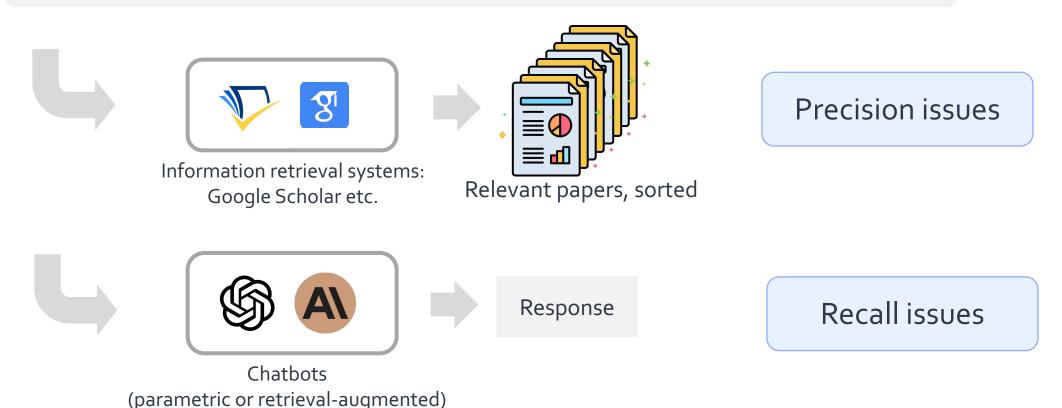


### Science queries: Information seeking vs Aggregative

Aggregative queries:



Query: Compare alignment approaches used in notable recent LLMs.



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# Not able to identify a meaningful set of column values (table schema)

ChatGPT

Create a table where the rows are recent language model and the columns are different details about their alignment process.

A lot of details are missing here! (many open-source models)

Here's a table summarizing recent language models and their alignment processes:

nguage Model	Alignment Process	Description
InstructGPT	Reinforcement Learning from Human Feedback (RLHF)	Trained to follow instructions by learning from human-provided feedback, enhancing its ability to align with user intentions.
ChatGPT	Reinforcement Learning from Human Feedback (RLHF)	Utilizes human feedback to fine-tune responses, aiming to improve relevance and appropriateness in conversational contexts.
Claude	Reinforcement Learning from AI Feedback (RLAIF)	Employs AI-generated feedback based on constitutional principles to guide its behavior, reducing reliance on human input.
Gemini	Reinforcement Learning from Human Feedback (RLHF)	Incorporates human feedback to align its outputs with user preferences, aiming for safer and more accurate responses.
Sparrow	Reinforcement Learning from Human Feedback (RLHF)	Focuses on aligning dialogue agents through targeted human judgments to improve safety and usefulness.
DeepSeek R1	Reinforcement Learning with Novel Training Methods	Introduces innovative training techniques that prioritize correct answers over human-legible reasoning, leading to unexpected behaviors.

Example retrieved on 02/27/2025

### What I manually created for my course:

Create a table where the rows are recent language model and the columns are different details about their alignment process.

Language Model	Release	Base	Alignment Algorithm(s) Used	Alignment Data Sources for alignment
GPT-3- instruct	2020	GPT-3	SFT> RLHF/PPO	Curated datasets with human-labeled prompts and responses
GPT-4	2023	GPT-4 pre- trained?	SFT> RLHF/PPO	Curated datasets with human-labeled prompts and responses
Gemini	2023	Gemini pre- trained?	SFT> RLHF/PPO	Curated datasets with human-labeled prompts and responses
LLaMA2	2023	LLaMA2 pre- trained	SFT> RLHF/PPO	Curated datasets with human-labeled prompts and responses
LLaMA3	2024	LLaMA3 pre-trained	Iterate: Rejection sampling -> SFT -> DPO	10 million human-annotated examples. The alignment process was conducted over multiple rounds, with each round involving the collection of new preference annotations and SFT data.
Alpacha	2023	LLAMA 1	SFT	Self-Instruct, 52,000 input-output pairs
Owen2.5	2024	Owen2.5 pre- trained	SFT -> DPO -> GRPO	1 million samples
Tulu 3	2024	Llama 3.1	SFT -> DPO -> RLVR	near 1 million samples
DeepSeek (V3)	2024	DeepSeek pre- trained	SFT -> GRPO	1.5 million samples (reasoning + non- reasoning tasks). Reasoning data was generated by specialized models. Non-reasoning data was produced by DeepSeek-V2.5 and validated by human reviewers.

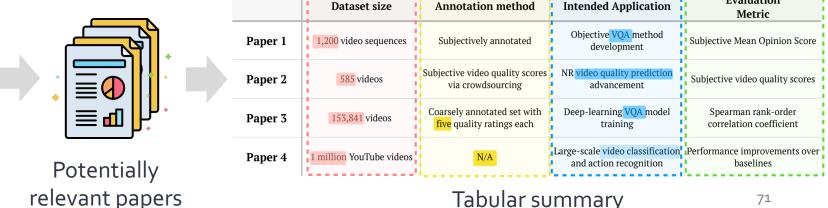
## arXiv2Table: A benchmark for aggregative questions

- 2.1K user demand prompts + tables (inherited from prior work).
- Evaluation framework based on utilization.

https://github.com/JHU-CLSP/arXiv2Table



**Prompt:** Generate a table comparing video datasets



**Evaluation** 

# Another type of aggregative questions: Distribution of science contributions

- Aggregative queries:
  - Query: How many papers are in Al?
  - Query: How many papers in AI are about extending RL?
  - Query: How many papers in AI are about extending DPO?
  - Query: How many papers use RL in surgical applications?

•

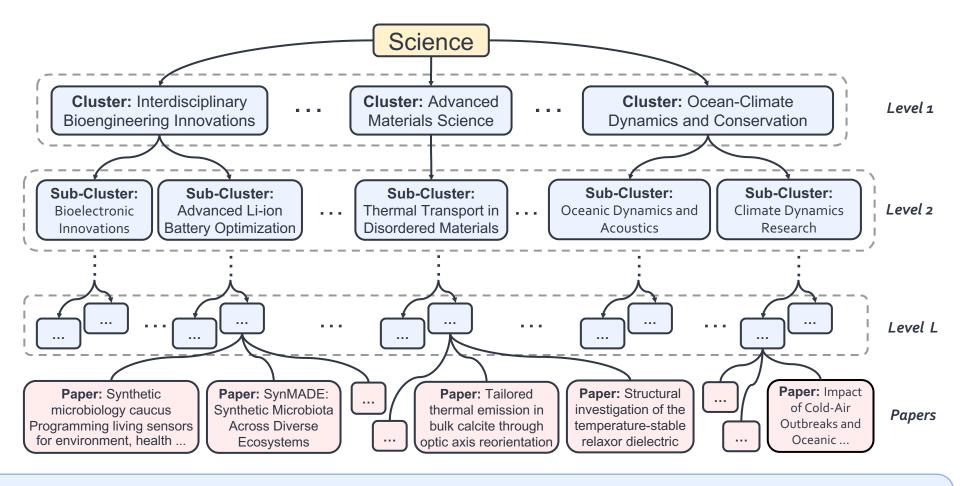
**Problem statement:** How do we compute the <u>distribution</u> of scientific efforts at varying levels of granularity?

### Distribution of science contributions: why?

- Why we should we care?
  - Allows us (e.g., policy makers) identify areas that are over/under-explored.
    - Necessary for ensuring effective investment in science.
  - Not just science! Many institutions (e.g., venture capital firms) need to understand the distribution of their investments.

**Problem statement:** How do we compute the <u>distribution</u> of scientific efforts at varying levels of granularity?

### An idealistic hierarchy of science

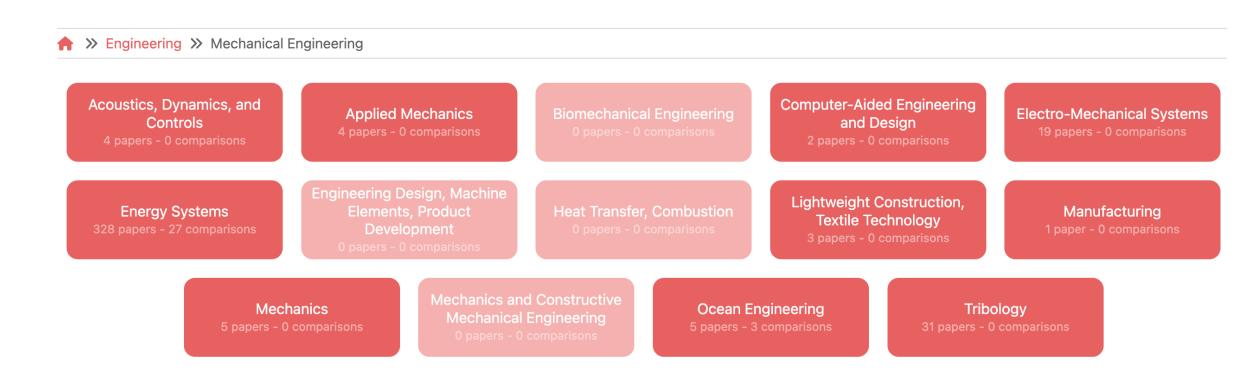


**Problem statement:** How do we compute the <u>distribution</u> of scientific efforts at varying levels of granularity?

### Existing hierarchies of science



- Manually curated with human curation
- They also have papers and their summaries within each category.



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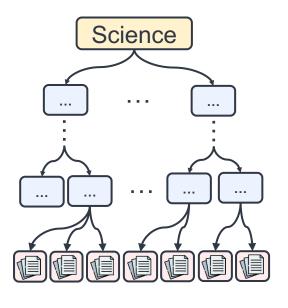
They have an ad for hiring people!!

ORKG CURATION GRANTS
RECEIVE 400 EURO MONTHLY
APPLICATION DEADLINE:
MAY 11TH, 2025

https://orkg.org/page/call-curation-grants-2025

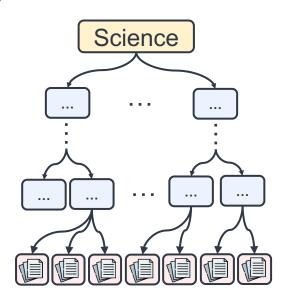
## Hierarchies of science paper

- 1. Representation of the node (what is a "paper"?)
- 2. Evaluating hierarchies
- 3. Inferring them



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# How do you represent a "paper"?

• We extract different contribution types from each paper:

### The Tin Pest Problem as a Test of Density Functionals Using High-Throughput Calculations

Michael J. Mehl,<sup>1,\*</sup> Mateo Ronquillo,<sup>2</sup> David Hicks,<sup>3</sup> Marco Esters,<sup>3</sup> Corey Oses,<sup>3</sup> Rico Friedrich,<sup>3</sup> Andriy Smolyanyuk,<sup>3</sup> Eric Gossett,<sup>3</sup> Daniel Finkenstadt,<sup>4</sup> and Stefano Curtarolo<sup>3,†</sup>

<sup>1</sup>Center for Autonomous Materials Design, Duke University, Durham NC 27708
 <sup>2</sup>U. S. Nuclear Power School, Goose Creek, South Carolina 29445
 <sup>3</sup>Center of Autonomous Materials Design, Duke University, Durham NC 27708
 <sup>4</sup>Physics Department, U.S. Naval Academy, Annapolis, Maryland 21402

 (Dated: October 15, 2020)

At ambient pressure tin transforms from its ground-state semi-metal  $\alpha$ -Sn (diamond structure) phase to the compact metallic  $\beta$ -Sn phase at 13°C (286K). There may be a further transition to the simple hexagonal  $\gamma$ -Sn above 450K. These relatively low transition temperatures are due to the small energy differences between the structures,  $\approx 20 \, \text{meV/atom}$  between  $\alpha$ - and  $\beta$ -Sn. This makes tin an exceptionally sensitive test of the accuracy of density functionals and computational methods. Here we use the high-throughput Automatic-FLOW (AFLOW) method to study the energetics of tin in multiple structures using a variety of density functionals. We look at the successes and deficiencies of each functional. As no functional is completely satisfactory, we look Hubbard U corrections and show that the Coulomb interaction can be chosen to predict the correct phase transition temperature. We also discuss the necessity of testing high-throughput calculations for convergence for systems with small energy differences.

https://arxiv.org/pdf/2010.07168





#### **Problem statement:**

- Problem domain
- Challenges
- Research goal

#### Solution:

- Approach
- Novelty

#### **Results:**

- Findings
- Impact

## How do you represent a "paper"?

• We extract different contribution types from each paper:

#### **Problem statement:**

- Problem domain: Condensed matter physics
- Challenges: Lack of full rotational symmetry in solids leading to new excitations beyond Dirac and Weyl fermions
- **Research goal:** Investigate sixfold excitations in electrides

GPT<sub>4</sub>



#### Solution:

- Approach: Propose that a single linear dispersive sixfold excitation can be found in the electride Li12Mq3Si4 and its derivatives
- Novelty: Unique topological bulk-surface-edge correspondence for the spinless sixfold excitation

#### **Results:**

- **Findings:** The sixfold excitation is formed by floating bands of elementary band representation A@12a. All gapped kz slices belong to a two-dimensional higher-order topological insulating phase, characterized by a quantized fractional corner charge Ocorner = 3|e|/4. Hinge arcs are obtained in the hinge spectra of the S4z-symmetric rod structure.
- Impact: Electrides are promising platforms for systematic studies of different topological phases.

e Tin Pest Problem as a Test of Density Functionals Using High-Throughpu Calculations

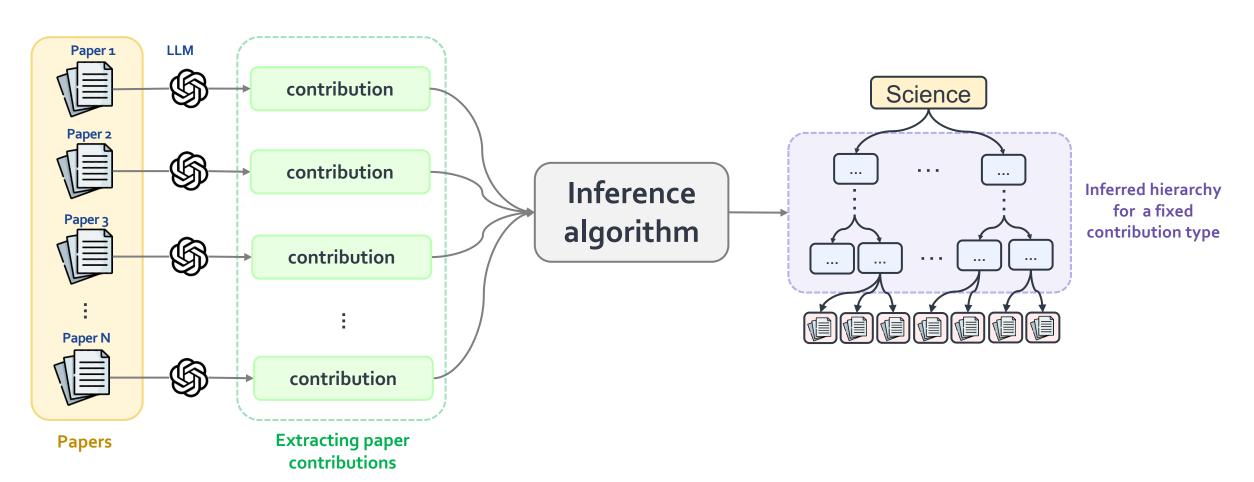
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Gao et al. Science Hierarchography: Hierarchical Abstractions of Scientific Literature.2025

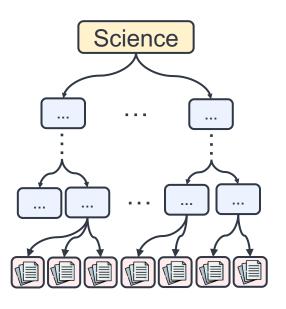
## One hierarchy per contribution type

• We extract different contribution types from each paper:



## Hierarchies of science paper

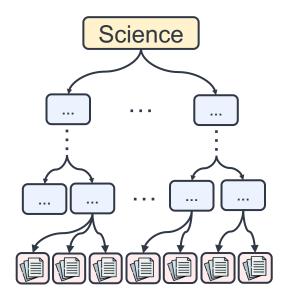
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### How should we evaluate a science hierarchy?

- There is no reference data for this task.
- Even if it did, it would need to be updated every few week!

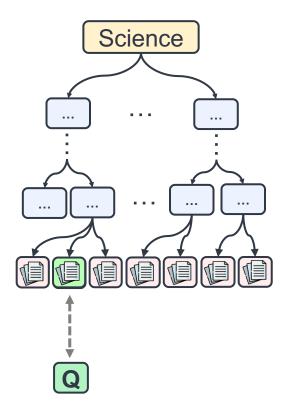
In absence of any gold standard, how can we evaluate a *given* hierarchy?



### Evaluation as Utilization

Idea: A good hierarchy allows one to identify things.

- Setup:
  - Input: A query that is answered at a leaf node.
  - Starting from root node, let a judge (an LLM) traverse the tree to identify the related leaf node.
- Metric: The accuracy of finding the relevant leaf.



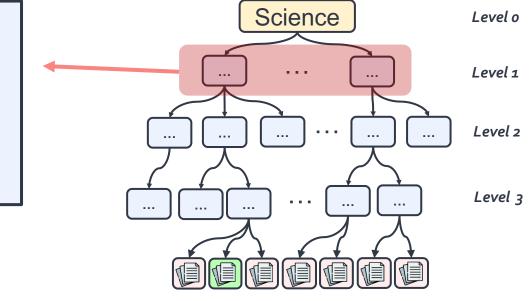
### Evaluation as Utilization: Example



Title: Controlling nonlinear interaction in a many-mode laser by tuning disorder Abstract: Many-mode lasers with nonlinear modal interaction can model many-body physics... We introduce random phase fluctuation to tune lasing modes...

#### Level 1 Clusters:

- 1. Materials for energy/env/health
- 2. Al for complex systems
- 3. Ocean & atmosphere dynamics
- 4. Topological & quantum materials
- 5. Photonic & quantum systems
- 6. Sustainable energy materials





The most appropriate cluster is:

5. Photonic & quantum systems

Owen2.5 (32B)

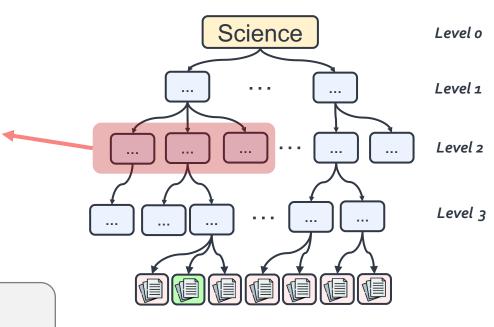
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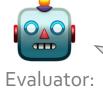


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#### Level 2 Clusters:

- 1. Advancements in Nano-Optical Resonance, Photonic Devices, and Nonlinear Optical Materials
- 2. Advances in Photonic Systems and Quantum Technologies for Enhanced Optical Control and Manipulation
- 3. Advancements in Quantum Optomechanics and Optical Physics for Enhanced Precision and Control
- 4. Advanced Photonic Technologies for Turbulence-Resilient Optical Communications and Wave Manipulation
- 5. Experimental Investigations of Quantum Gravity and Macroscopic Quantum Systems





The most appropriate cluster is:

1. Advancements in Nano-Optical Resonance, Photonic Devices, and Nonlinear Optical Materials

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### Evaluation as Utilization: Example



Title: Controlling nonlinear interaction in a many-mode laser by tuning disorder Abstract: Many-mode lasers with nonlinear modal interaction can model many-body physics... We introduce random phase fluctuation to tune lasing modes...

#### Level 3 Clusters:

- 1. Advancements in Nano-Optical Resonance and Photonic Devices
- Advanced Nanophotonic Materials and Metamaterials for Enhanced Optical Interactions
- 3. Advancements in Nonlinear Photonics and Quantum Optics
- 4. Advanced Optical Materials and Phenomena for Enhanced Metrology and Control
- 5. Advanced Nonlinear Optical Materials and Photonics

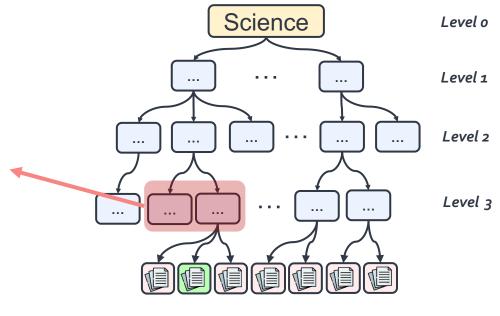


Evaluator:

Owen2.5 (32B)

The most appropriate cluster is:

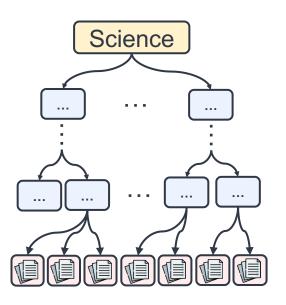
3 - Advancements in Nonlinear Photonics and Quantum Optics



A good hierarchy allows one to identify things!

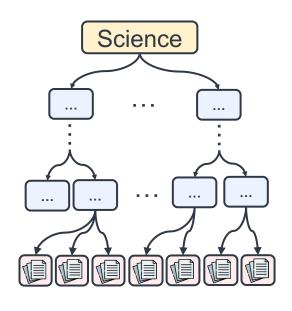
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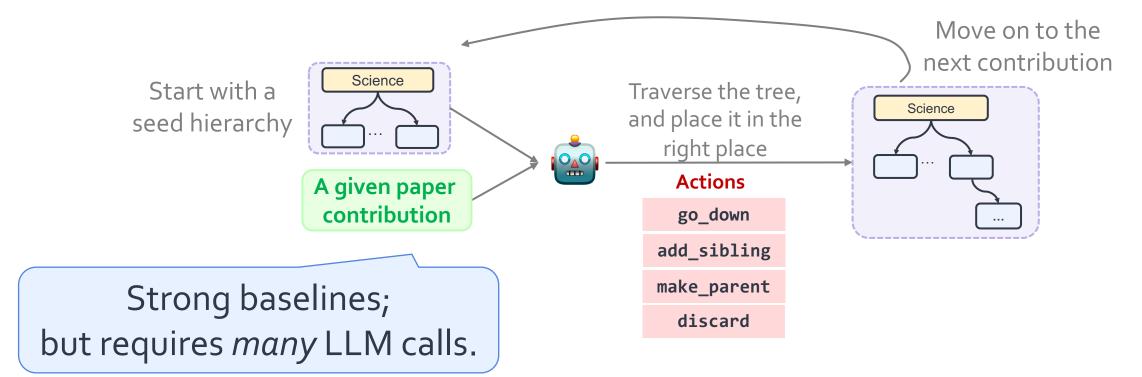
### Can LLMs solve this?

- LLMs are good at local decisions (if they're common).
  - Example: RL is a variant of Al.
- Challenges :
  - The task here requires a global coherence, but you cannot fit the whole hierarchy/papers in the context.
  - A lot of science is part of the long-tail where LLMs are less reliable.



### Pure-LLM based approaches

• Approach: Place one item at a time in a seed hierarchy.

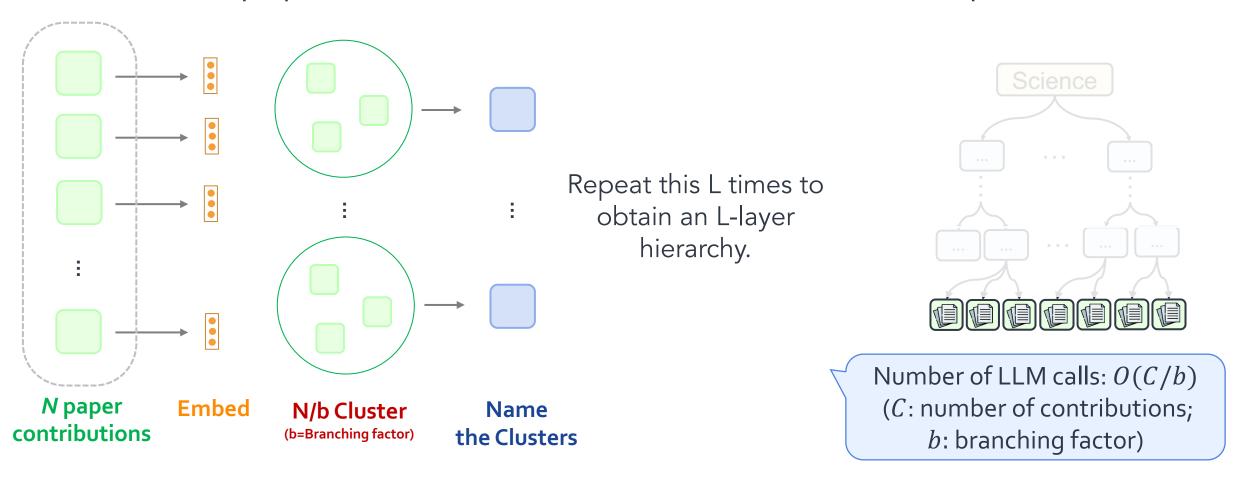


 $O(C \cdot \log C)$ 

(*C*: number of contributions)

# Scychic: Combining LLM and Clustering

Cluster papers and then name with LLMs (bottom-up)



### Evaluation

- A semi-random set of 2K papers
  - (results on 10K papers in the paper)

Scychic has high accuracy while requiring much less LLM calls.

The task is difficult. Help us solve it!

• Examples here: <a href="https://ia1.wse.jhu.edu/port4000/">https://ia1.wse.jhu.edu/port4000/</a>

Method	Accuracy ↑	# of LLM Calls ↓
Contributions type: Top	vic	
SCYCHIC	14.9	
↓Top-down	14.9	322
└Bottom-up	13.9	
Pure LLM baseline	18.0	61K
Contributions type: Pro	oblem Statement	
SCYCHIC	51.1	
¬Top-down	49.0	322
<b>Bottom-up</b>	45.9	
Contributions type: Soi	lution Statemen	t
SCYCHIC	48.8	
<b>Top-down</b>	45.9	322
4 Bottom-up	14.8	
Contributions type: Re	sults Statement	
SCYCHIC	46.4	
<b>Top-down</b>	45.2	322
-Bottom-up	40.0	
·		

### Putting things together

• Motivation: Aggregative queries that require understanding the distribution of scientific efforts across different sub-areas.

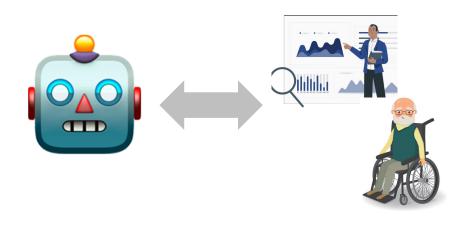
- Science Hierarchography: Large-scale hierarchical summarization of scientific literature.
- We proposed framework to
  - 1. Evaluate: measuring hierarchy quality, in absence of gold data.
  - 2. Infer hierarchies: balancing quality and scalability. Far from perfect!

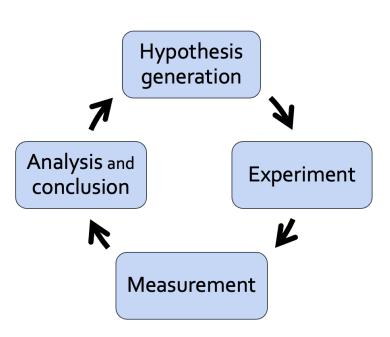
### Al for facilitating science: how far are we?

- LLM have brought up massive opportunities to speed up science.
  - Accessing and digesting, reviewing, ...
- Not just LLMs— we should think about "systems" that are built upon them. There are many other challenges remain here.
- At the same time, LMs are brittle and likely to remain brittle.
  - We need innovative ways to scope them and contain their brittleness.

## Not AGI: Helpful agents w/ bounded autonomy

- Systems that are robust within well-defined domain, might be better alternatives to generalist brittle models.
  - Growing LLMs as part of data ecosystem





- It's more helpful to pursue scoped agents that augment us.
  - Not to replace us.

### Thanks for wonderful collaborators on these projects:

