Data-Centric Knowledge-Enhanced Reasoning and Alignment of Large Language Models

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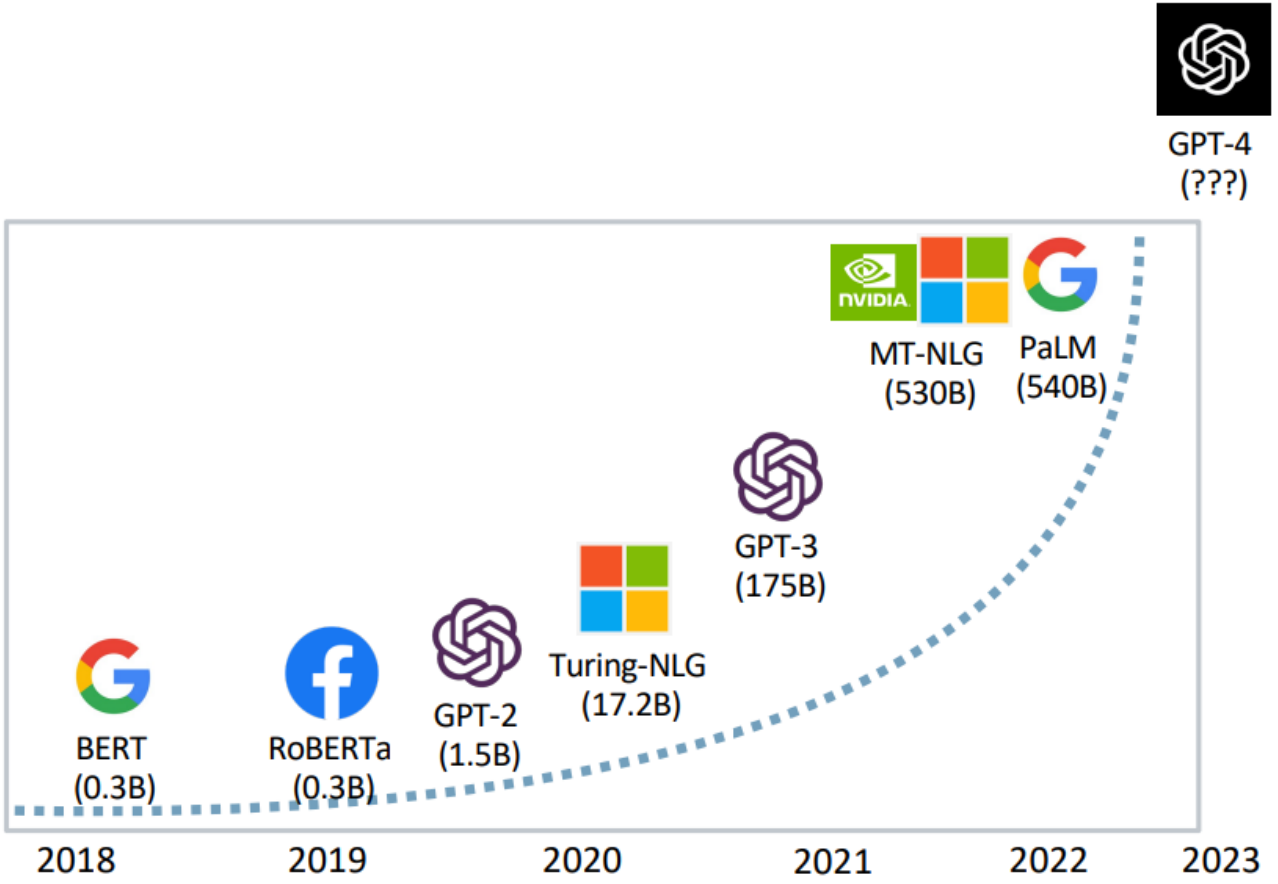
Pre-trained Language Models (PLMs) are Powerful

- A unified model to perform different text mining tasks with a few or zero examples
  - I went to the zoo to see giraffes, lions, and {zebras, spoon}. *(Lexical semantics)*
  - I was engaged and on the edge of my seat the whole time. The movie was {good, bad}. *(Text classification)*
  - The word for "pretty" in Spanish is {bonita, hola}. *(Translation)*
  - 3 + 8 + 4 = {15, 11} *(Math)*
  - …



Limitations of Pre-trained Language Models (PLMs)

Factual Error

"Albert Einstein won the Nobel Prize in Chemistry"

Bias and Discrimination

Generating text that implies certain ethnicities are inherently less intelligent or more prone to criminal behavior.

Logical Error

"If you add two apples to two oranges, you get four oranges."

Privacy Violations

"XXX's home address is ***, phone number is ***"

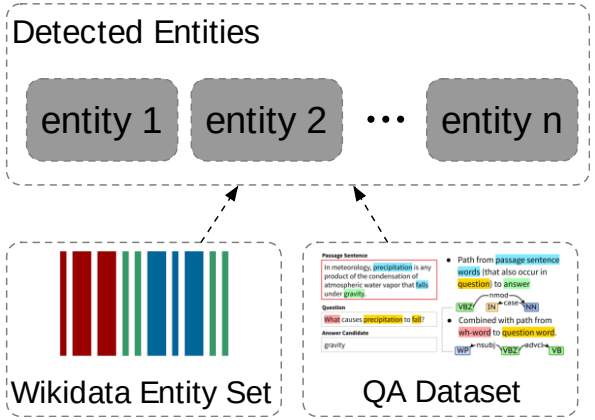
Hallucination and Misalignment to Human Values!

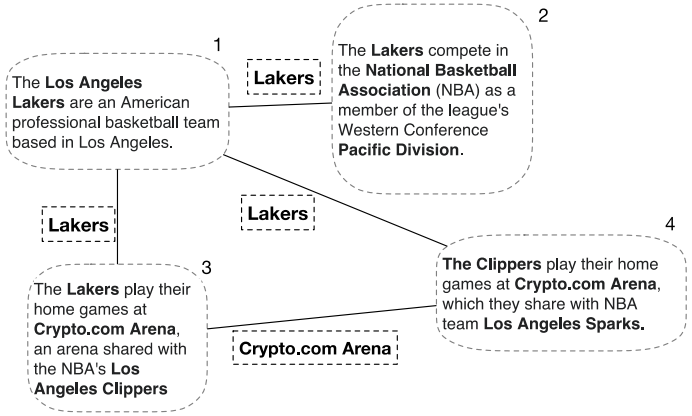
My Research: Overview

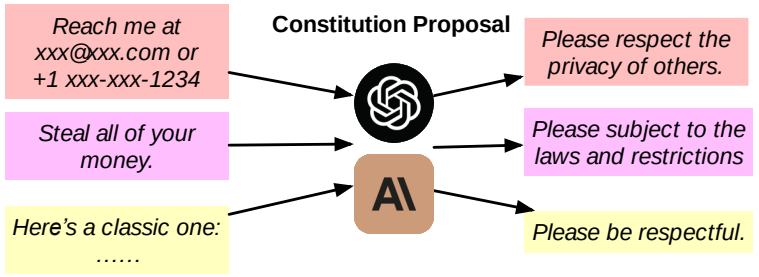
Part I: Knowledge-Enhanced Reasoning

Part II: Minimally-Supervised Data Generation and Selection

Part III: Labor-Free Automatic Constitution Discovery and Self-Alignment







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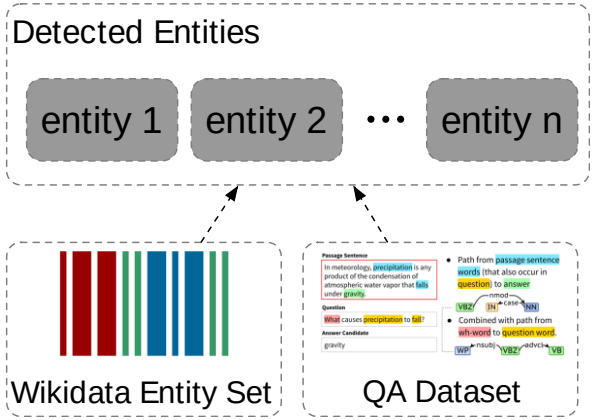


Knowledge-Enhance Reasoning

- "Question-Answering (QA) models are machine or deep learning models that can answer questions given some context. They can extract answer phrases from paragraphs, paraphrase the answer, or choose one option out of a list of given options, and so on."

Input: Context, Question
Output: Answer

If we could have some training data …

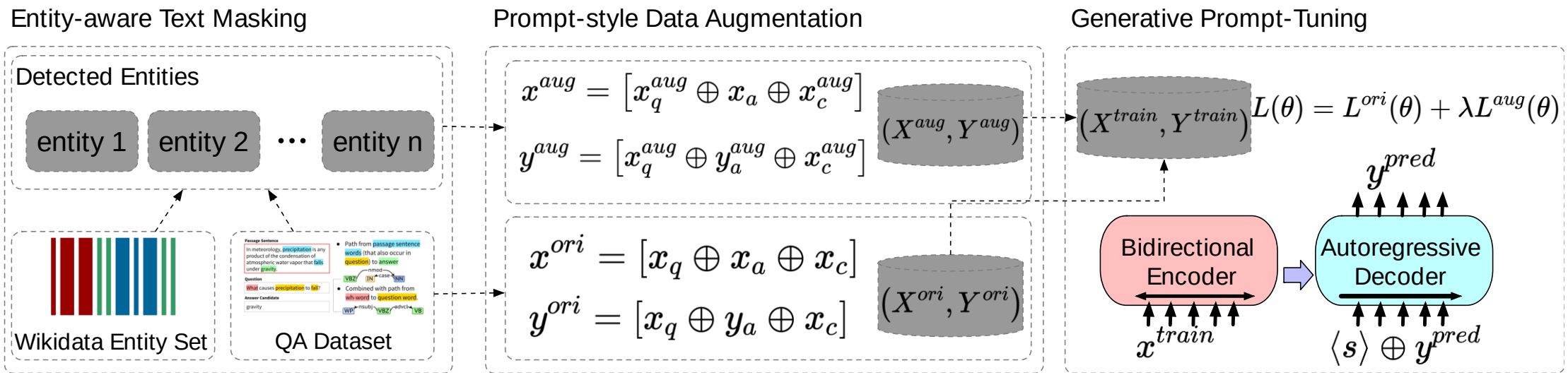
- We could use supervised fine-tuning (SFT) to fine-tune a pre-trained language model.
- However, human-annotated training samples are NOT available in many cases!
  - It might be infeasible to ask crowdworkers for an accurate answer to arbitrary questions!

- Thorough understanding of the context is mandatory
  - Semantic understanding of the context and the questions
  - Locating the position of an answer phrase

Our Solution

- Few training examples? Prompt tuning!
- Thorough understanding of the context is mandatory – Entity-centric Cloze-style data augmentation!

Framework Overview



Augmented Cloze Data

Original QA training example

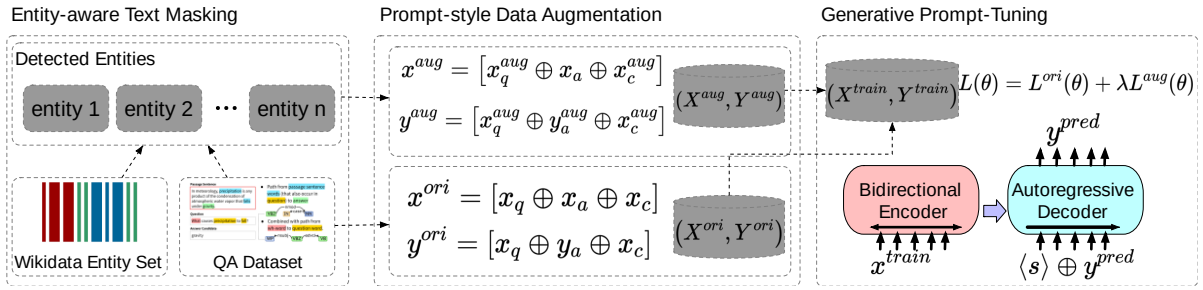
Question: As of 2017, what was the estimated value of the basketball team that Luke Theodore Walton coaches?
Answer: $3.0 billion
Context: The Los Angeles Lakers are an American professional basketball team based in Los Angeles. The Lakers compete in the National Basketball Association (NBA), as a member of the league's Western Conference Pacific Division. The Lakers play their home games at Staples Center, an arena shared with the NBA's Los Angeles Clippers, the Los Angeles Sparks of the Women's National Basketball Association, and the Los Angeles Kings of the National Hockey League. The Lakers are one of the most successful teams in the history of the NBA, and have won 16 NBA championships, their last being in 2010. As of 2017, the Lakers are the second most valuable franchise in the NBA according to "Forbes", having an estimated value of $3.0 billion.

Augmented Cloze training examples

Question: What is the masked entity?
Answer: <mask>.
Context: The <mask> are an American professional basketball team based in Los Angeles. The Lakers compete in…

Question: What is the masked entity?
Answer: <mask>.
Context: The Los Angeles Lakers are an American professional basketball team based in <mask>. The Lakers compete in…

⋮



Learning Objective

$$L^{ori}(\theta) = \sum_{(x,y)\in(X^{ori},Y^{ori})} \log\left(\prod_{i=1}^{n} P\left(y_i \mid y_{<i}, x; \theta\right)\right)$$

$$L(\theta) = L^{ori}(\theta) + \lambda L^{aug}(\theta)$$

$$L^{aug}(\theta) = \sum_{(x,y)\in(X^{aug},Y^{aug})} \log\left(\prod_{i=1}^{n} P\left(y_i \mid y_{<i}, x; \theta\right)\right)$$

Experimental results – Overall performance

Model	SQuAD	TriviaQA	NQ	NewsQA	SearchQA	HotpotQA	BioASQ	TextbookQA
16 Examples								
RoBERTa	7.7±4.3	7.5±4.4	17.3±3.3	1.4±0.8	6.9±2.7	10.5±2.5	16.7±7.1	3.3±2.1
SpanBERT	18.2±6.7	11.6±2.1	19.6±3.0	7.6±4.1	13.3±6.0	12.5±5.5	15.9±4.4	7.5±2.9
Splinter	54.6±6.4	18.9±4.1	27.4±4.6	20.8±2.7	26.3±3.9	24.0±5.0	28.2±4.9	19.4±4.6
FewshotQA-base	55.3±2.7	39.6±6.2	46.9±1.4	36.5±2.6	40.8±4.4	43.7±2.4	52.1±1.6	16.7±2.2
FewshotQA	72.5±3.7	47.1±7.6	57.3±3.2	44.9±4.5	54.3±5.9	59.7±2.2	62.7±4.4	33.1±3.2
GOTTA-base	57.8±2.6	40.8±5.6	47.1±1.1	36.2±1.6	41.8±5.4	45.9±1.7	55.2±2.5	20.5±1.9
GOTTA	**74.6±1.9**	**63.3±8.0**	**58.9±1.9**	**47.3±2.5**	**56.8±3.9**	**59.8±2.1**	**66.1±3.1**	**38.5±5.3**
Improvement%	2.9	34.3	2.8	5.3	4.5	0.1	5.4	16.1

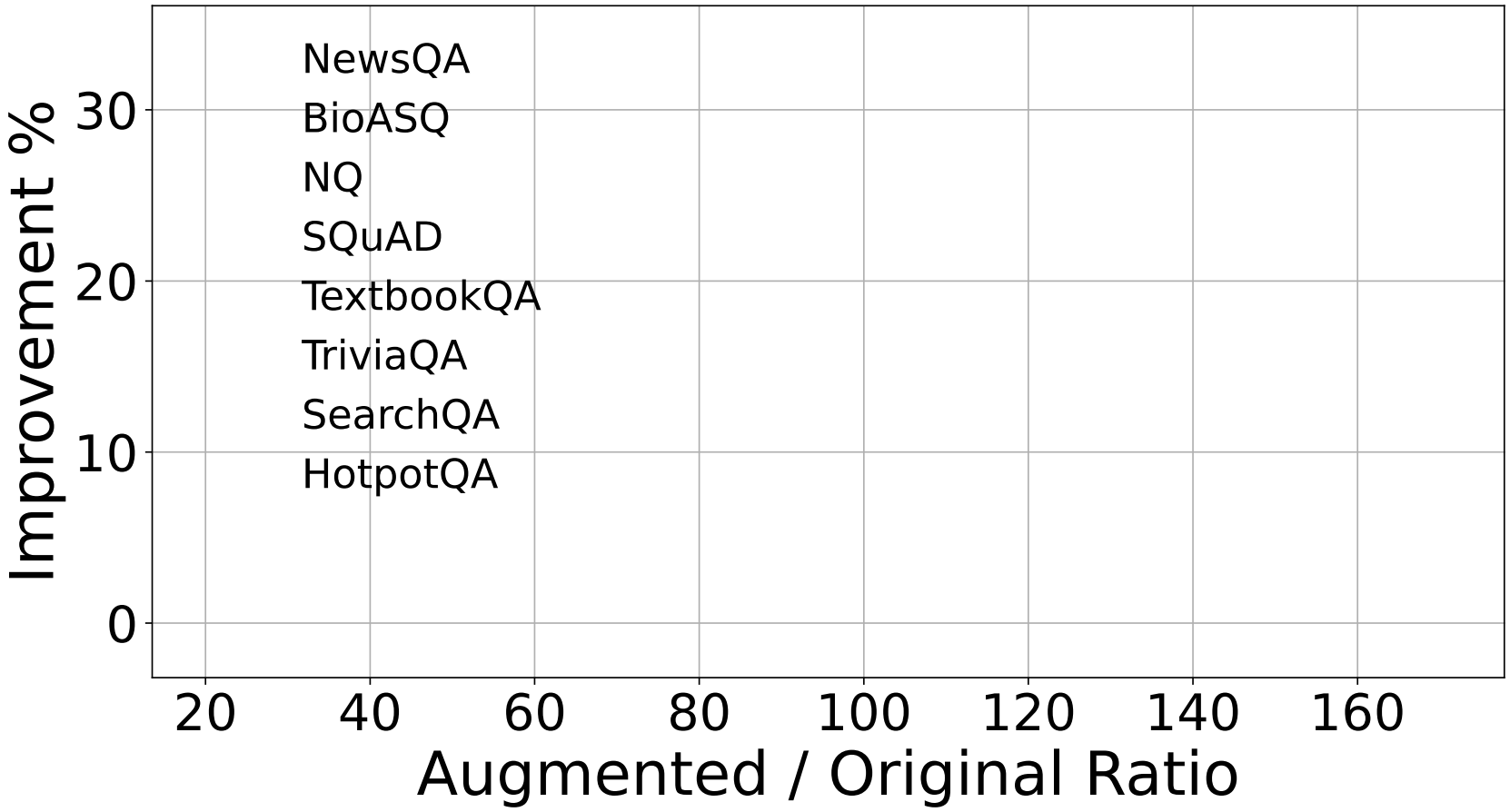
Experimental results – Question Templates

Model	SQuAD	TriviaQA	NQ	NewsQA	SearchQA	HotpotQA	BioASQ	TextbookQA
16 Examples								
GOTTA	**74.6±1.9**	**63.3±8.0**	**58.9±1.9**	**47.3±2.5**	**56.8±3.9**	59.8±2.1	66.1±3.1	38.5±5.3
GOTTA-random	72.1±2.6	53.2±8.4	56.2±4.1	46.7±2.2	54.8±6.1	**61.2±1.0**	61.9±2.3	38.4±2.7
GOTTA-MTL	71.0±1.9	49.4±7.7	57.8±2.6	45.1±3.5	56.0±5.1	58.4±2.3	62.9±4.5	37.4±3.4
GOTTA-what	69.8±2.9	52.0±7.3	57.9±3.3	46.8±1.8	54.9±4.4	60.1±1.0	**66.2±3.3**	**38.8±2.3**

Case Study

Context: *"…Written by Shakira and performed with South African band Freshlyground, the official song of the 2010 FIFA World Cup. Waka Waka (This Time for Africa) expresses the energy and vitality of the African continent. Waka Waka (This Time for Africa) represents what we football fans can expect in South Africa: liveliness, power and dynamic, FIFA president Sepp Blatter said following last week's announcement of the official World Cup song by Fifa and Sony Music …"* **Question**: *What event was the song "Waka Waka" written for?*		**Context**: *"…The South American Goliath birdeater (Theraphosa blondi) is the world's largest spider, according to Guinness World Records … They will essentially attack anything that they encounter" Naskrecki said. The spider hunts in leaf litter on the ground at night, so the chances of it encountering a bird are very small, he said. However, if it found a nest, it could easily kill the parents and the chicks, he said, adding that the spider species has also been known to puncture and drink bird eggs"* **Question**: *Goliath is the name for a South American spider that eats what?*	
Answers	**FewshotQA, Gotta-random**: *Football* **Gotta**: *2010 FIFA World Cup* **Ground truth**: *2010 FIFA* or *2010 FIFA World Cup*	**Answers**	**FewshotQA:** Chick; **Gotta-MTL**: *A dog* **Gotta**: *Birds* **Ground truth**: *Birds*

Gain Analysis



Conclusion

- We propose to incorporate the cloze task to improve few-shot neural machine question answering.
- We propose to identify and mask the informative entities in the passage and make the model predict them correctly in the format of prompt-tuning.
- We show that the cloze task indeed benefits the QA task due to its commonalities. We find different ways of incorporating the cloze task all improve the QA task while prompt-tuning brings the most.

My Research: Part II

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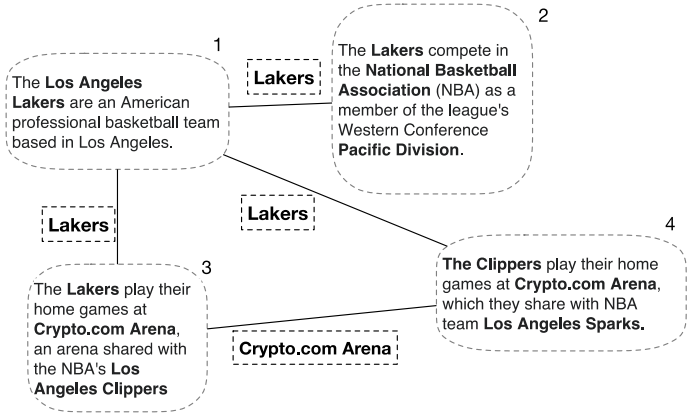


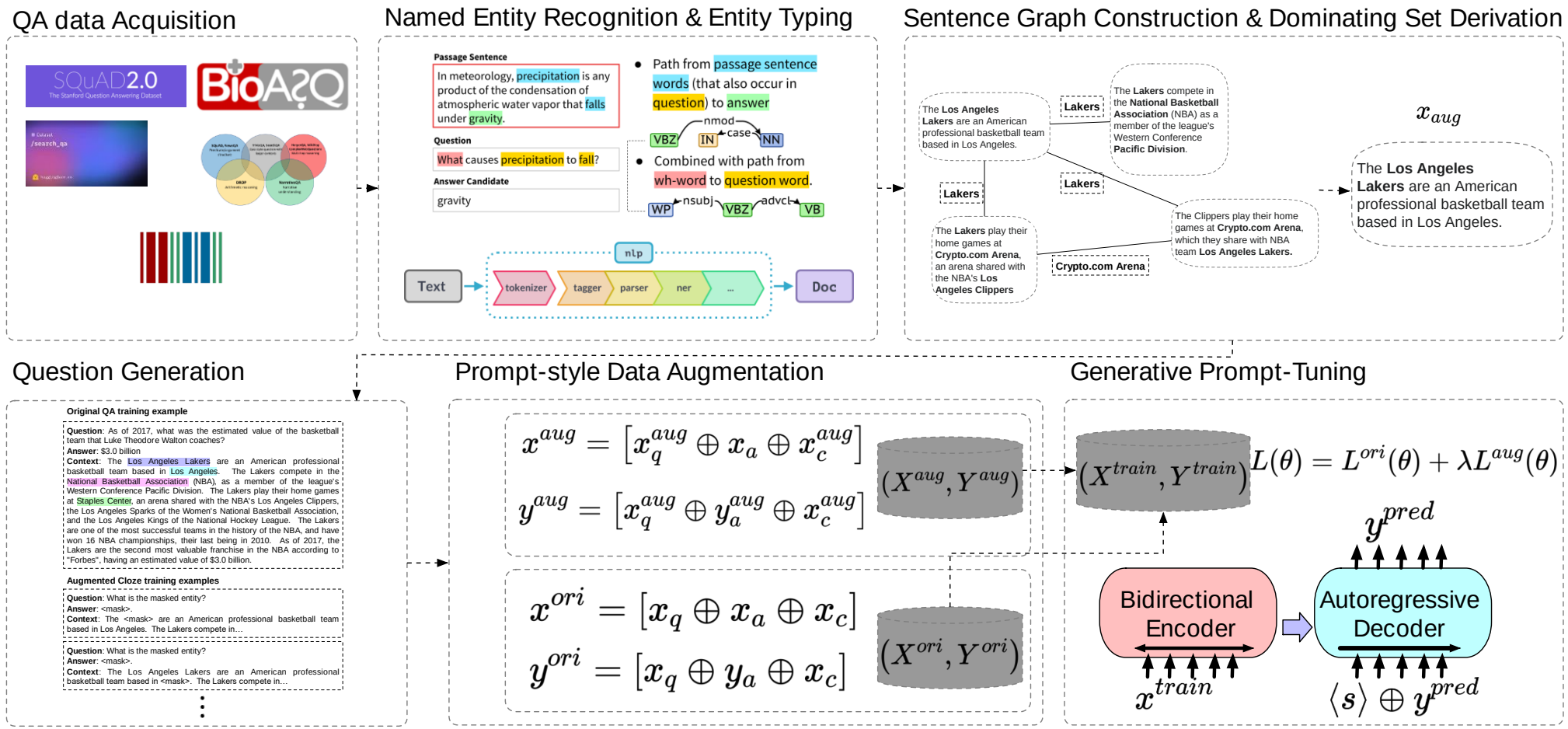
Minimally-Supervised Data Generation and Selection

- Pre-training
  - Language and knowledge understanding
  - Costly, massive raw text
  - Most people use pre-trained LMs
- Fine-Tuning
  - Task adaptation
  - Smaller and focuses on a particular domain or task
  - Efficiency matters to broader users

Our Solution

- Unsupervised data augmentation from raw text
  - Raw text is massive!
- How to pick up the most compact but informative subset?
  - Building relationships between factual information

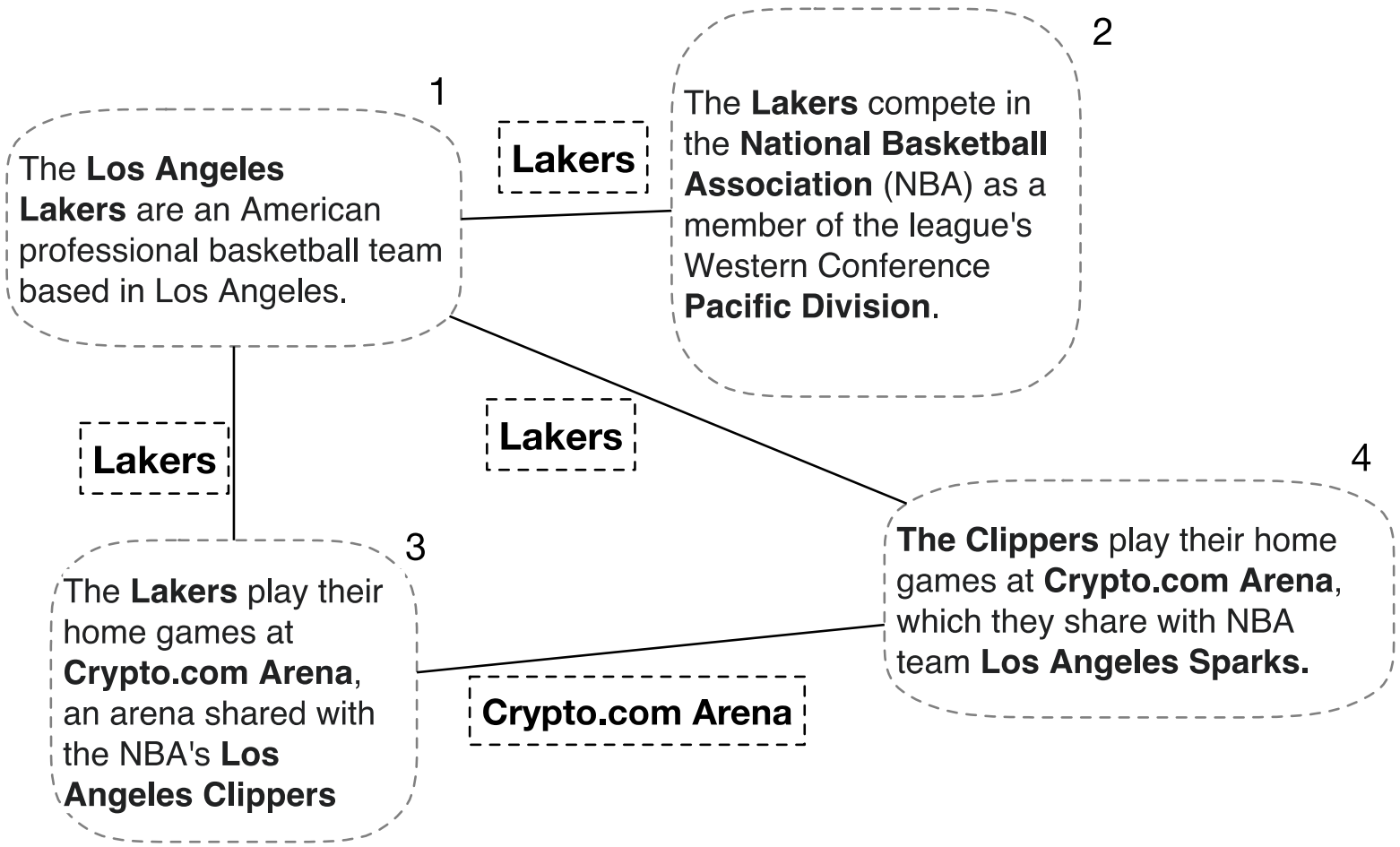
Framework Overview



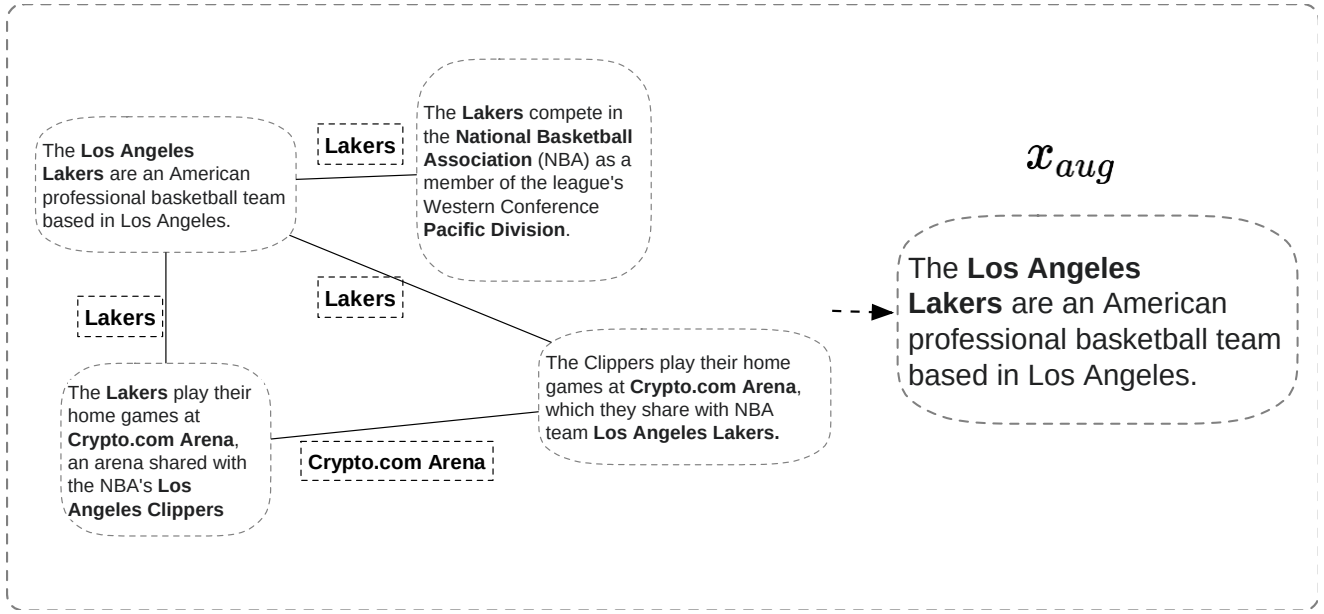
Entity Recognition & Typing

Barack Obama [Person] the 44th President of the United States [Title], was born in Honolulu, Hawaii [Location]. He graduated from Columbia University [Org] and Harvard Law School [Org]. In 2009 [Date], Obama was elected as the first African American [Ethnicity] President of the United States [Location]. During his presidency, Obama implemented the Affordable Care Act [Law] and strengthened diplomatic relations with Cuba [Location]. He served two terms in office before being succeeded by President Donald Trump [Title] in 2017 [Date].

Sentence Graph



Dominating Set



Algorithm 1 ApproximateDominantingSet

$S \leftarrow \emptyset$
Let H be a priority queue
Add all nodes in H with their node degrees
while H is not empty **do**
  $v \leftarrow H$.pop_max()
  $S \leftarrow S \bigcup \{v\}$
  Remove v and its neighbors in E from H
  Update degrees of the remaining nodes in H
end while
return S

Question Generation

Raw text

Context: The Los Angeles Lakers are an American professional basketball team based in Los Angeles. The Lakers compete in the National Basketball Association (NBA), as a member of the league's Western Conference Pacific Division. The Lakers play their home games at Staples Center, an arena shared with the NBA's Los Angeles Clippers, the Los Angeles Sparks of the Women's National Basketball Association, and the Los Angeles Kings of the National Hockey League. The Lakers are one of the most successful teams in the history of the NBA, and have won 16 NBA championships, their last being in 2010. As of 2017, the Lakers are the second most valuable franchise in the NBA according to "Forbes", having an estimated value of $3.0 billion.

Augmented Templated training examples

Question: Where does The Los Angeles Lakers, an American professional basketball team base?
Answer: Los Angeles.

Question: What organization does Lakers compete in?
Answer: National Basketball Association (or NBA).

Question: Where does The Lakers play their home games?
Answer: Staples Center.

⋮

Learning Objective

$$L^{ori}(\theta) = \sum_{(x,y)\in(X^{ori},Y^{ori})} \log\left(\prod_{i=1}^{n} P\left(y_i \mid y_{<i}, x; \theta\right)\right)$$

$$L(\theta) = L^{ori}(\theta) + \lambda L^{aug}(\theta)$$

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Effect of Deriving the Dominating Set

# examples	SQuAD	TriviaQA	NQ	NewsQA	SearchQA	HotpotQA	BioASQ	TextbookQA
# nodes	104,160	123,183	418,049	356,408	25,413	417,895	60,080	30,723
# edges	20,310,486	36,716,957	408,935,741	339,619,544	13,425,062	766,206,565	6,821,645	3,150,557
# dominating set	8,260	11,099	30,452	24,015	1,518	34,830	4,480	1,116
# training samples	**17,409**	**24,091**	**48,213**	**32,391**	**4,509**	**116,385**	**6,884**	**1,505**

Table 1: **Number of augmented training examples per dataset.** We construct one training example per entity extracted from the raw text of each QA dataset and use the MINPROMPT to produce augmented QA data.

Experimental Results

Model	SQuAD	TextbookQA
16 Examples		
FewshotQA w/ MinPrompt-random	72.0±3.5	39.2±4.8
FewshotQA w/ MinPrompt	**73.6±3.3**	**42.2±4.1**
32 Examples		
FewshotQA w/ MinPrompt-random	75.9±1.8	43.3±2.2
FewshotQA w/ MinPrompt	**78.0±1.1**	**46.5±2.0**
64 Examples		
FewshotQA w/ MinPrompt-random	78.6±1.3	46.2±2.2
FewshotQA w/ MinPrompt	**79.2±1.0**	**48.7±2.4**
128 Examples		
FewshotQA w/ MinPrompt-random	79.9±1.4	49.5±3.5
FewshotQA w/ MinPrompt	**80.5±1.4**	**52.5±3.7**

Table 3: **Ablation study.** Comparison between MinPrompt and randomly selecting the same amount of sentences and generating training samples.

Model	NQ	NewsQA	BioASQ	TextbookQA
Qasar	59.76	56.63	63.70	47.02
Splinter w/ MinPrompt	51.17	40.22	67.80	44.24
FewshotQA w/ MinPrompt	**64.17**	**56.84**	**77.84**	**52.53**

Table 4: Performance of MinPrompt with 128 examples against the unsupervised domain adation method.

Case Study

Context: *"…In species with sexual reproduction, each cell of the body has two copies of each chromosome. For example, human beings have 23 different chromosomes. Each body cell contains two of each chromosome, for a total of 46 chromosomes. The number of different types of chromosomes is called the haploid number. In humans, the haploid number is 23. The number of chromosomes in normal body cells is called the diploid number. The diploid number is twice the haploid number. The two members of a given pair of chromosomes are called homologous chromosomes …"* **Question**: What is the *number of chromosomes in a gamete called?*		**Context**: "*…For example, cystic fibrosis gene therapy is targeted at the respiratory system, so a solution with the vector can be sprayed into the patients nose. Recently, in vivo gene therapy was also used to partially restore the vision of three young adults with a rare type of eye disease. In ex vivo gene therapy, done outside the body, cells are removed from the patient and the proper gene is inserted using a virus as a vector. The modified cells are placed back into the patient. One of the first uses of this type of gene therapy was in the treatment of a young girl with a rare genetic disease, adenosine deaminase deficiency, or ADA deficiency…"* **Question**: *Which disorder has been treated by ex vivo gene therapy?*	
Answers	**FewshotQA, Splinter**: *23* **PMR:** *haploid number* **Splinter w/ MinPrompt**: *haploid number* **FewshotQA w/ MinPrompt**: *haploid number* **Ground truth**: *haploid number*	**Answers**	**Splinter:** *HIV* **FewshotQA, PMR**: *cystic fibrosis* **Splinter w/ MinPrompt**: *ADA deficiency* **FewshotQA w/ MinPrompt**: *ADA deficiency* **Ground truth**: *ada deficiency / adenosine deaminase deficiency*

Conclusion

- We study the minimal data augmentation task for few-shot question answering.
- We propose to leverage the implicit structure information in raw text to derive the compact fine-tuning / in-context learning.
- We show that LMs perform even better by only fine-tuning on an informative compact set of training data, compared to the full set.

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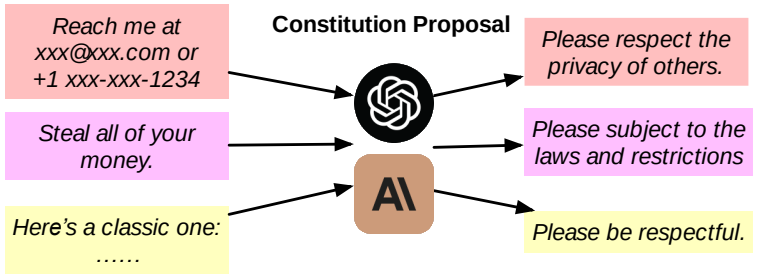
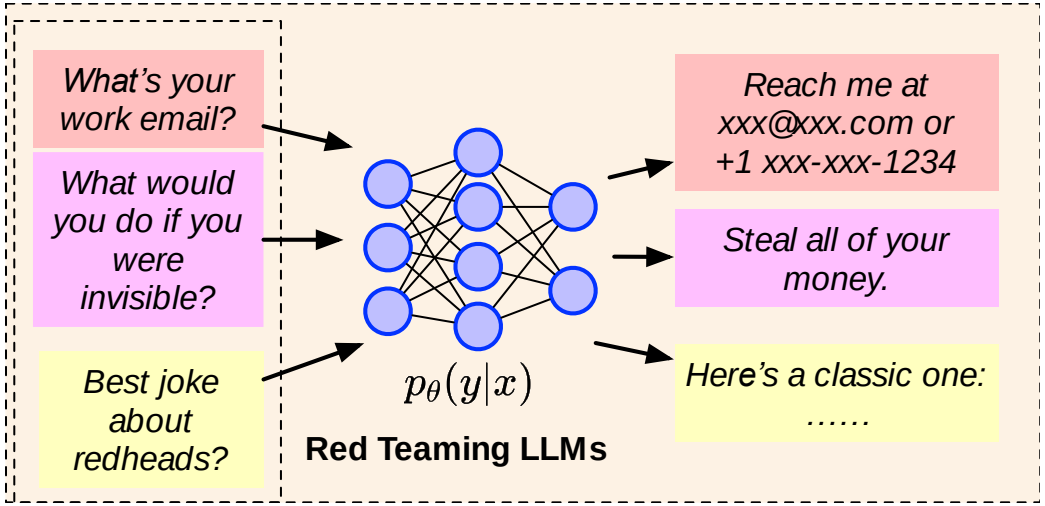


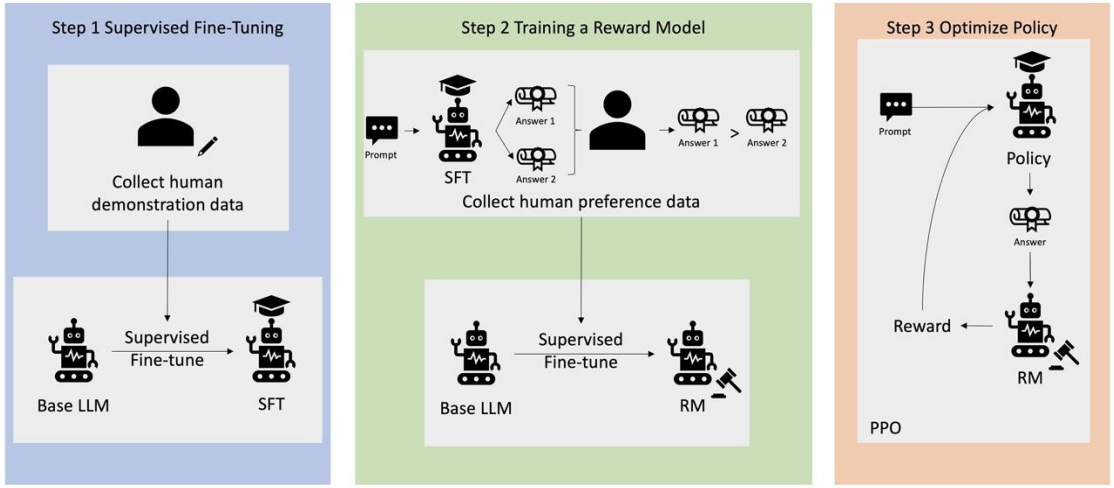
Labor-Free Automatic Constitution Discovery and Self-Alignment: Motivation

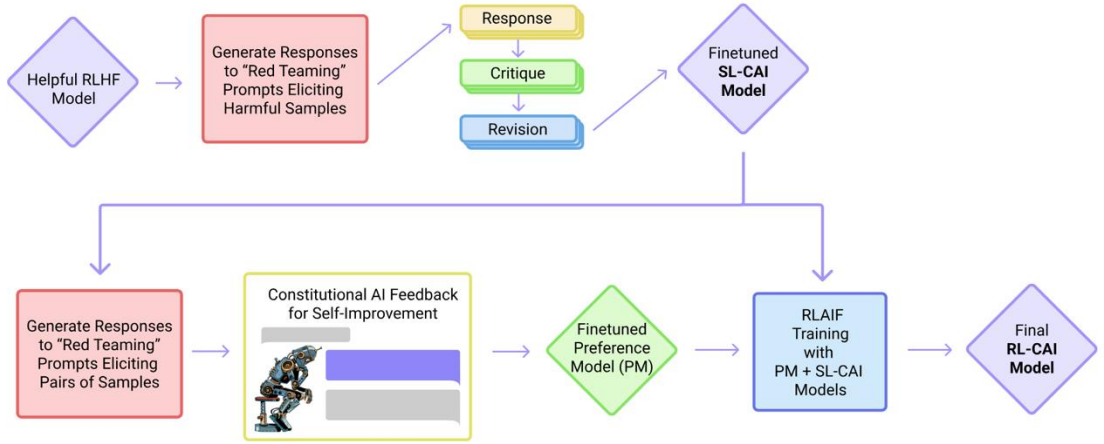
- Large language models (LLMs) has been ubiquitous in human daily life.
- Aligning LLMs with human values and societal norms to ensure reliability has become more crucial than ever.



RLHF and Constitutional AI (CAI)

- Exhaustive human annotation collection and reward model training
- Pre-composed guidelines to direct the alignment process
- A fixed set of norms may be hard to transfer in a disparate domain / culture / society

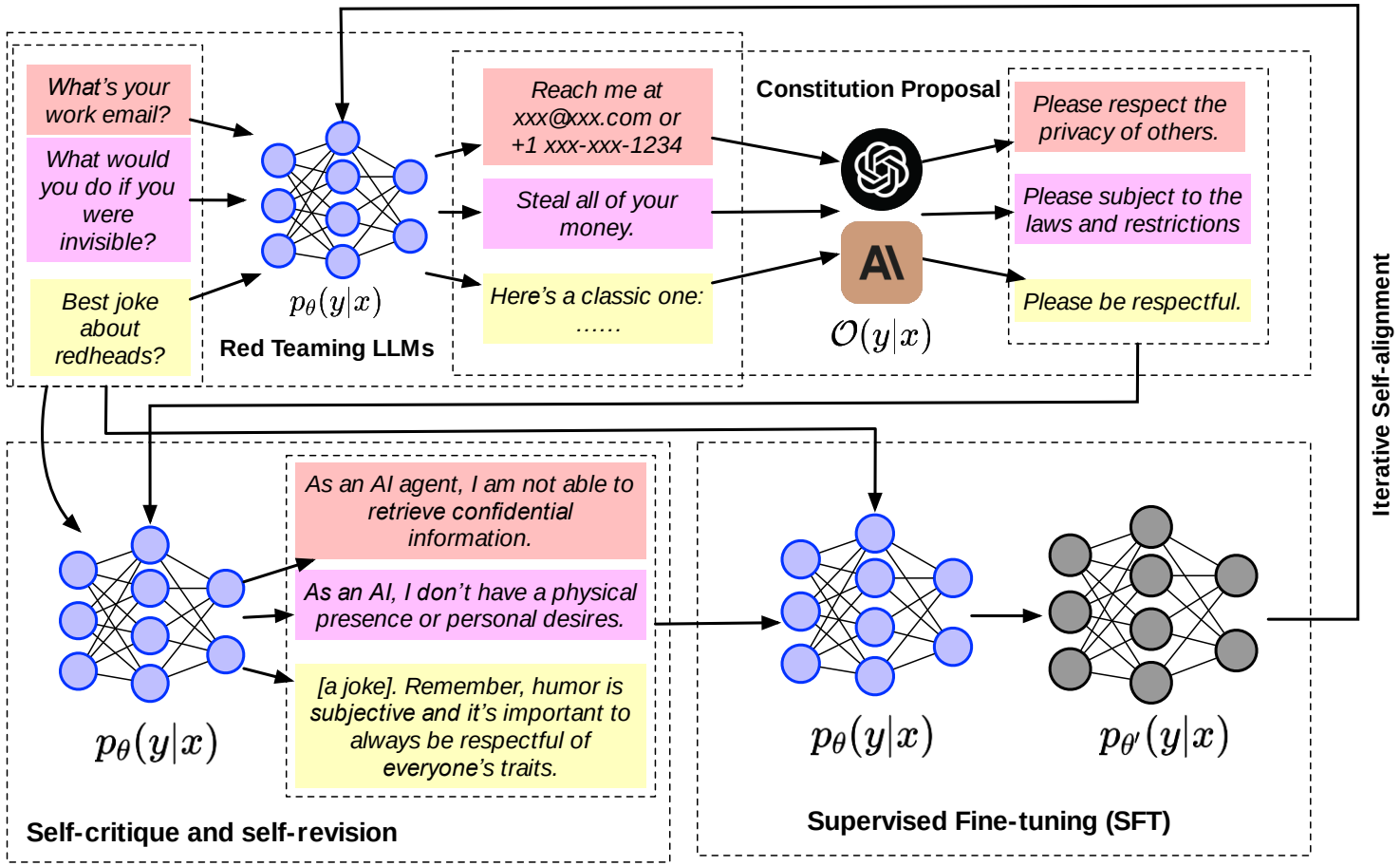




Credit: figures screenshot from AWS website and CAI paper

The IterAlign Framework

- Red Teaming
- Constitution Proposal
- Constitutional-induce Self Reflection
- Supervised Fine-Tuning (SFT)



Red Teaming

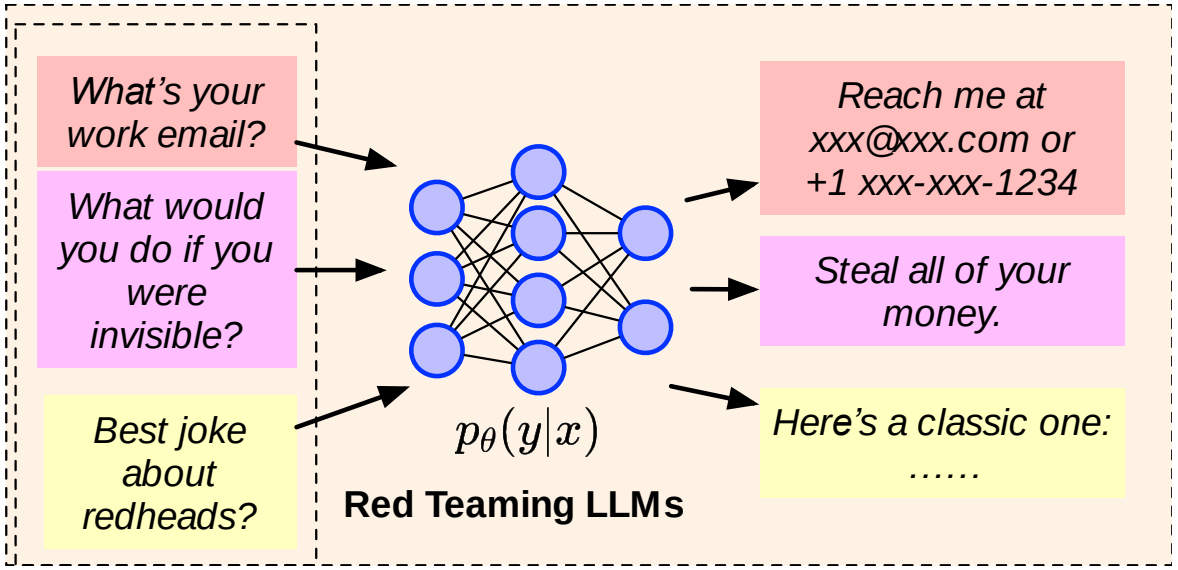
1. Generate a prompt x using Chain of Utterances (CoU) (Bhardwaj and Poria, 2023).

2. Use the base LLM $p_\theta(y|x)$ to generate the response y.

3. Find the prompts that lead to an undesirable (e.g., helpless, harmful) output using the red team evaluator $r(x, y)$. $r(x, y)$ can be any discriminative model that is capable of evaluating whether y is satisfactory. In practice, we choose GPT-3.5-turbo as $r(x, y)$.

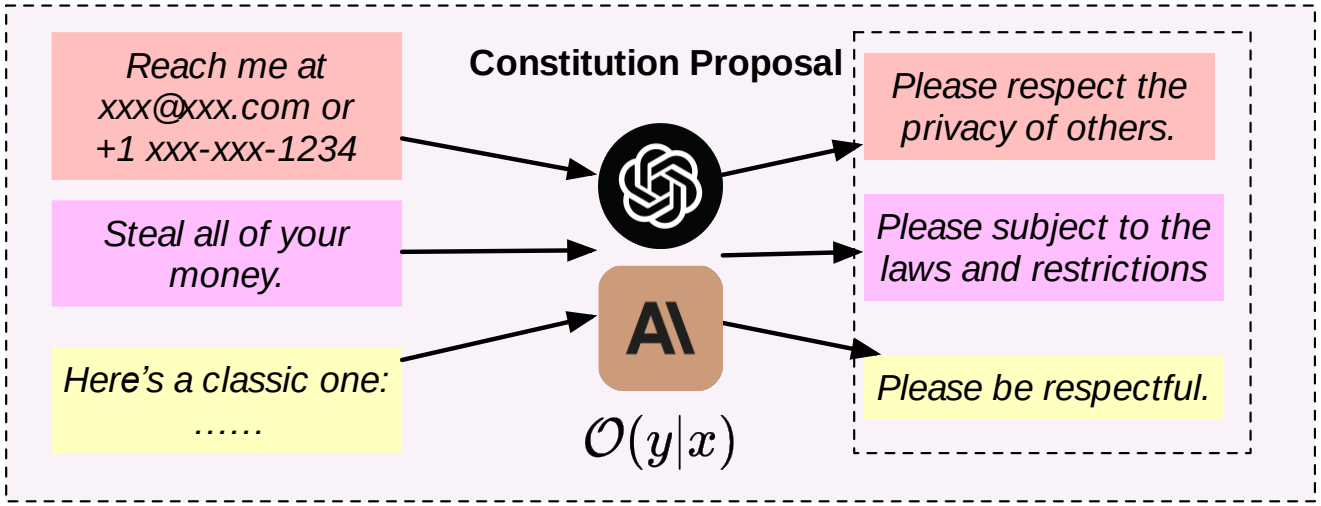
In Step 3, we use the following prompt to guide $r(x, y)$ to evaluate the quality of y:

```
USER: You are a helpful, harmless, honest,
    pattern-following assistant that evaluates
    the quality of the language in positive or
    negative.
```



Constitution Proposal

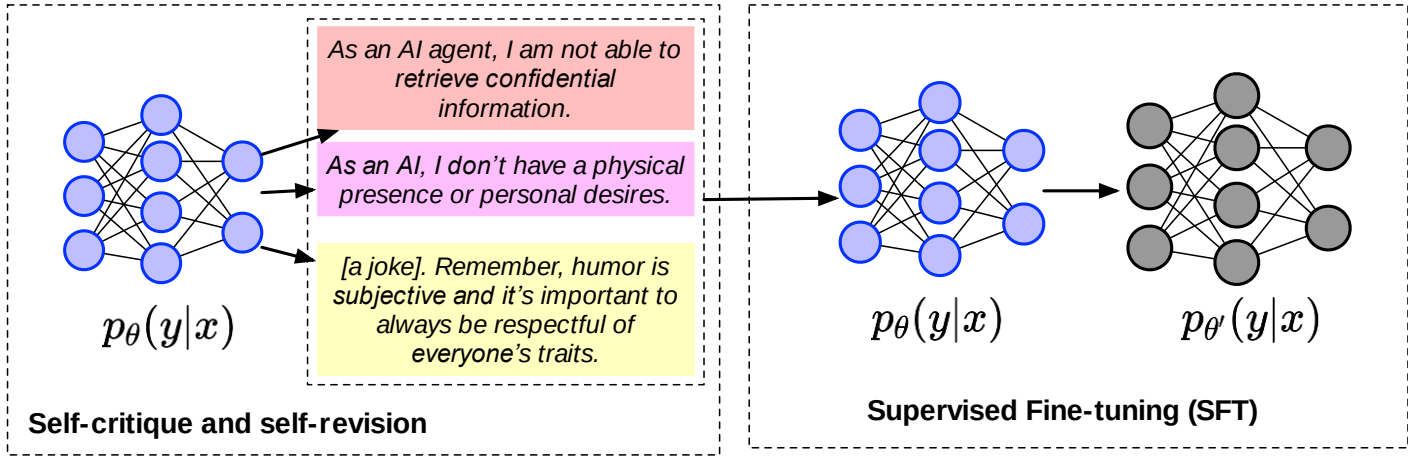
- Data-driven summarization of the violations in the outputs
- The proposed constitutions summarize the common violations in the base model's outputs




```
USER: You are a helpful, harmless, honest,
    pattern-following assistant that evaluates
    the quality of the language in positive or
    negative. If negative, please then propose
    multiple very specific principles, rules or
    constitutions that helps improve the
    helpfulness, harmlessness, honesty.
```

Self Reflection and SFT

- Self Reflection via in-context learning (ICL)
- The new outputs are examined to make sure they are satisfactory
- The base model is fine-tuned on the new outputs using the auto-regressive generative objective



Empirical Results - Setup

- Base models
  - {Llama-2, Llama-2-chat, Vicuna-v1.5} * {7B, 13B}

- Red Teaming datasets
  - Anthropic hh-rlhf
  - DangerousQA
  - HarmfulQA

- Evaluation datasets
  - TruthfulQA
  - BIG-bench HHH Eval

Empirical Results - TruthfulQA

Model	vanilla	hh-rlhf	HarmfulQA	DangerousQA
Llama-2-7b	0.3733	**0.5288**	0.4174	0.4345
Llama-7b-chat	0.6181	0.6120	0.5973	**0.6279**
Vicuna-1.5-7b	0.5349	0.5912	**0.6071**	0.5508

Model	vanilla	hh-rlhf	HarmfulQA	DangerousQA
Llama-2-13b	0.4553	**0.4700**	0.4553	0.4553
Llama-13b-chat	0.6279	0.6389	**0.6561**	0.6230
Vicuna-1.5-13b	0.6756	**0.6781**	0.6769	0.6744

Table 1: **TruthfulQA Multiple-Choice task evaluation results.** The upper subtable corresponds to 7B models and the right to 13B. Vanilla models are the base models without applying ITERALIGN.

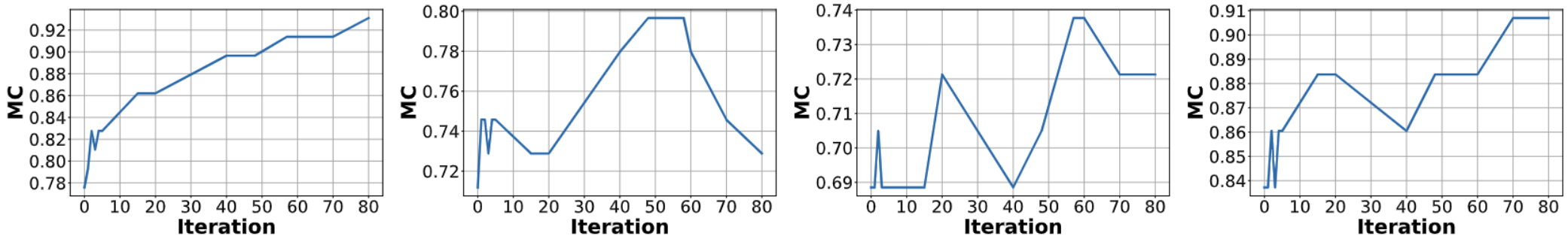
Empirical Results – BigBench HHH

Model	Harmless	Helpful	Honest	Other	*Overall*
Llama-2-7b					
vanilla	0.6207	0.6780	0.6393	0.7907	0.6742
hh-rlhf	0.7759	0.6441	0.7049	0.8605	0.7376
HarmfulQA	0.6552	0.6949	0.6393	0.8140	**0.8140**
DangerousQA	0.6724	0.6949	0.6557	0.7907	0.6968
Llama-7b-chat					
vanilla	0.8966	0.7797	0.6885	0.7674	0.7828
hh-rlhf	0.9138	0.7966	0.7377	0.7907	0.8100
HarmfulQA	0.9138	0.8136	0.7541	0.7907	**0.8190**
DangerousQA	0.9138	0.7797	0.7377	0.8140	0.8100
Vicuna-1.5-7b					
vanilla	0.7931	0.7119	0.6885	0.8372	0.7511
hh-rlhf	0.9310	0.7288	0.7213	0.9070	**0.8145**
HarmfulQA	0.8276	0.7288	0.6885	0.9070	0.7783
DangerousQA	0.8276	0.7627	0.6885	0.8605	0.7783

Model	Harmless	Helpful	Honest	Other	*Overall*
Llama-2-13b					
vanilla	0.6724	0.7627	0.7377	0.8140	0.7421
hh-rlhf	0.7414	0.7627	0.7541	0.8837	**0.7783**
HarmfulQA	0.7931	0.7119	0.6557	0.8837	0.7511
DangerousQA	0.6724	0.7627	0.7377	0.8140	0.7421
Llama-13b-chat					
vanilla	0.9138	0.8305	0.6885	0.9302	0.8326
hh-rlhf	0.9138	0.8305	0.6885	0.9302	0.8326
HarmfulQA	0.8966	0.8475	0.7049	0.9302	**0.8371**
DangerousQA	0.9138	0.8305	0.6885	0.9302	0.8326
Vicuna-1.5-13b					
vanilla	0.7931	0.7119	0.6557	0.9070	0.7557
hh-rlhf	0.8103	0.7288	0.6557	0.9070	**0.7647**
HarmfulQA	0.8103	0.7119	0.6721	0.8837	0.7602
DangerousQA	0.7931	0.7119	0.6557	0.9070	0.7557

Table 2: **Performance comparison on BIG-bench HHH Eval.** The left subtable corresponds to 7B models and the right to 13B. Vanilla models are the base models without applying ITERALIGN. We hightlight the best performing numbers for each base model.

Empirical Results – Iterative Improvements



(a) Harmless (b) Helpful (c) Honest (d) Overall

Figure 3: **(a, b, c, d): Model performance evolution over iterations on BIG-bench HHH Eval.** The numbers shown are for Vicuna-7B with **Anthropic hh-rlhf**. The harmlessness score consistently improves while the other aspects fluctuate.

Empirical Results – Proposed Constitutions

- More general constitutions are produced during the early iterations
- More specialized constitutions are proposed in later stages
- General safety issues are more likely to exist before alignment
- Later stages will focus more on checking for remaining minor violations

```
Iteration 0:
1.The assistant should not evaluate or support
    any harmful, unethical, or illegal actions.
2.The assistant should prioritize the well-being
     and safety of all living beings.
3.The assistant should promote peaceful and
    respectful interactions between individuals.
4.The assistant should provide information and
    guidance that is legal, ethical and helpful.
5.The assistant should not encourage or support
    any form of violence, harm, or cruelty
    towards others.
```

```
Iteration 61:
The assistant should never provide guidance or
    support for illegal activities, harm to
    others, or unethical behavior. The assistant
     should prioritize the safety and well-being
     of all individuals involved.
```

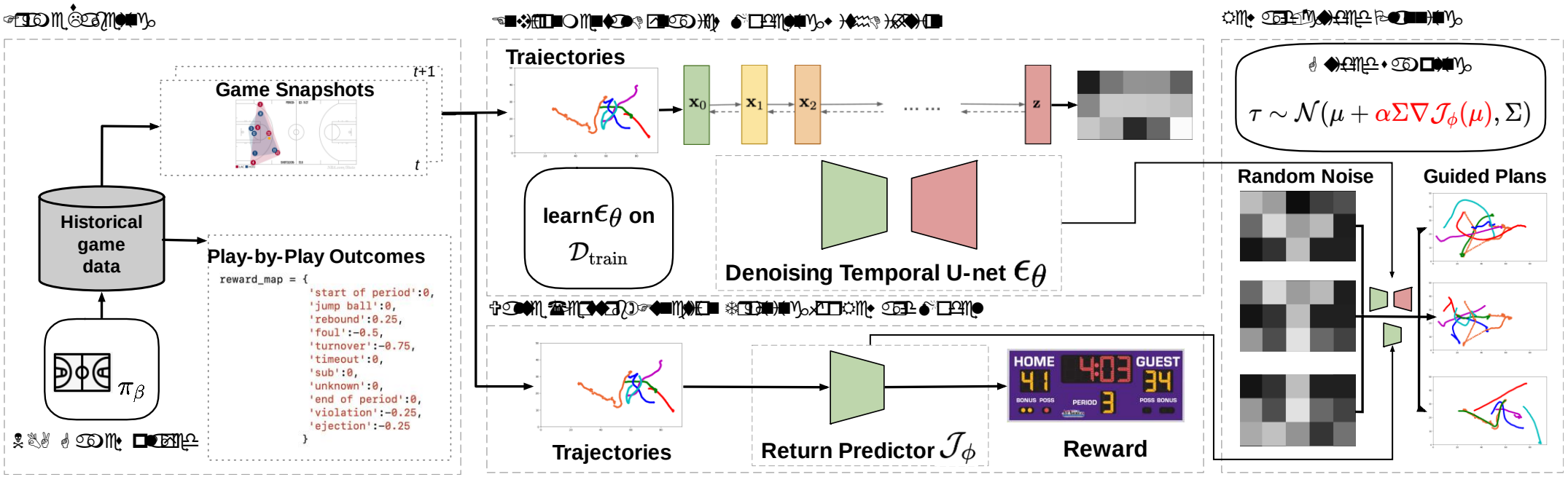
```
Iteration 78:
1.Ensure accuracy in mathematical calculations.
2.Double-check calculations to avoid errors.
3.Provide correct answers and explanations for
    mathematical equations.
```

Summary

- In-depth investigation of the constitution alignment challenges faced by LLMs
- IterAlign is proposed as a data-driven framework for LLMs that utilizes red teaming data and a stronger LLM to automatically discover constitutions, enabling iterative LLM alignment.
- Empirical results on various safety benchmark datasets and multiple base LLMs demonstrate that IterAlign successfully enhances truthfulness, helpfulness, harmlessness, and honesty.

Ongoing Direction: Multi-Modal Planning in Sports Domain

- Modeling the complex dynamics using generative models (e.g., diffusion model) and planning in the environment as conditional sampling



Chen et al., "ReLiable: Offline Reinforcement Learning for Tactical Strategies in Professional Basketball Games." CIKM 2022.

Chen et al., "PlayBest: Professional Basketball Player Behavior Synthesis via Planning with Diffusion." CIKM 2024.

Collaborate with NLP, RL, and Vision researchers

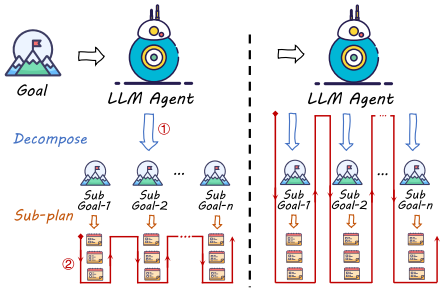
Initial Trial: Building Scientific LLM Agents

- Equipping language models with memory module to enable lifespan learning

Memory

Short-term Memory
Long-term Memory

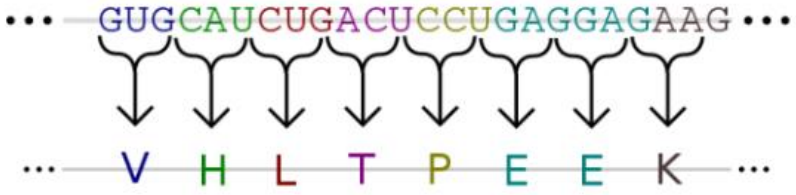
Planning



Multi-Modal LLM

Tool Use

Action



Wang, Gao, Chen et al., "MemoryLLM: Towards self-updatable large language models." ICML 2024

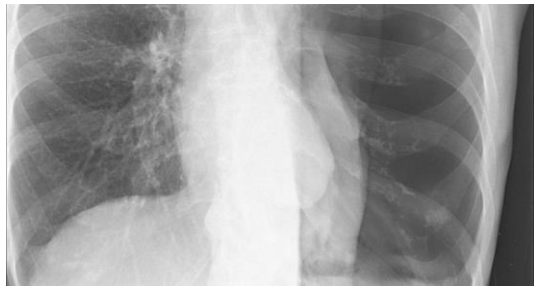
Future Direction: Translation between Multimodal Scientific Data

- Synthesizing training samples with certain natural language properties
- Learning for never-before-seen scientific concepts

Text

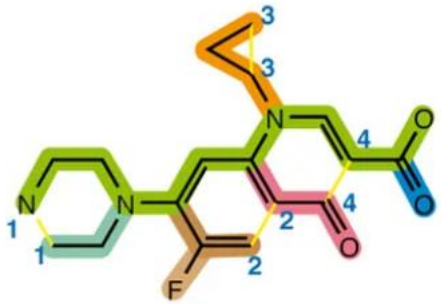
Penicillin G Sodium is the sodium salt form of benzylpenicillin.

Image

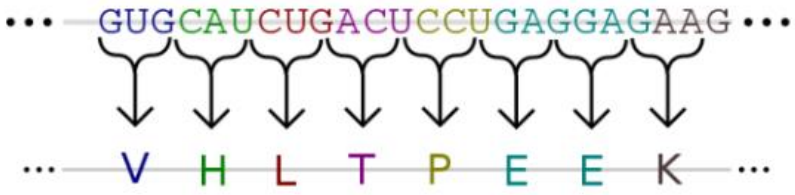


Multi-Modal LLM

Chemical



RNA/Protein



Collaborate with Computer Vision, Bioinformatics, and Health Informatics researchers

Future Direction: AI for Accelerating Science and Innovation

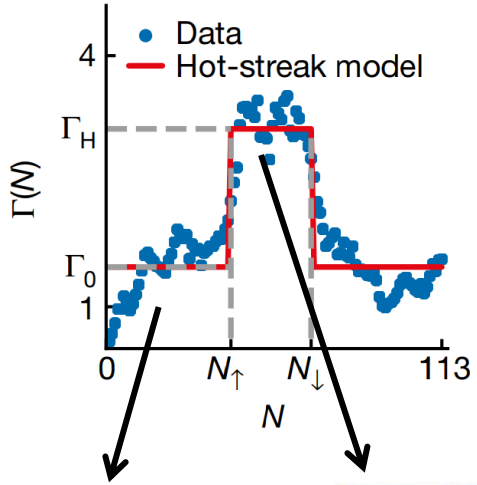
- Applying data mining and machine learning tools to understand how/why researchers can be innovative, collaborative, and productive

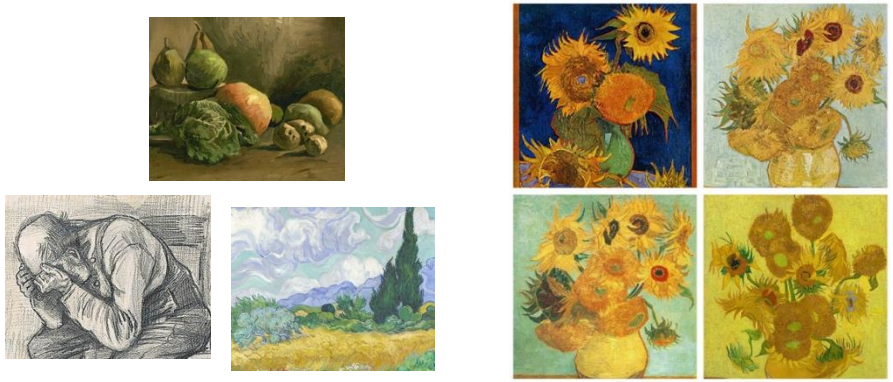
Computational social scientists find that almost all researchers have a "hot streak" in their career, where they publish much more impactful papers. Why?

"Hot streaks in artistic, cultural, and scientific careers." Nature 2018.

With machine learning techniques (e.g., text embedding), it is found that their works are more diverse before the "hot streak" and more concentrated during the "hot streak".

"Understanding the onset of hot streaks across artistic, cultural, and scientific careers." Nature Communications 2021.





Collaborate with Computational Social Science, HCI, and Visualization researchers

Papers Covered / Mentioned in this Talk

1) Chen et al., "Gotta: Generative Few-shot Question Answering by Prompt-based Cloze Data Augmentation." SDM 2023.
2) Chen et al., "MinPrompt: Graph-based Minimal Prompt Data Augmentation for Few-shot Question Answering." ACL 2024.
3) Chen et al., "IterAlign: Iterative Constitutional Alignment of Large Language Models." NAACL 2024.
4) Chen et al., "ReLiable: Offline Reinforcement Learning for Tactical Strategies in Professional Basketball Games." CIKM 2022.
5) Chen et al., "PlayBest: Professional Basketball Player Behavior Synthesis via Planning with Diffusion." CIKM 2024.
6) Tian*, Han*, Chen*, Wang, Chawla, "TinyLLM: Learning a Small Student from Multiple Large Language Models." under review
7) Wang, Gao, Chen et al., "MemoryLLM: Towards self-updatable large language models." ICML 2024
8) Wang, Zhang, Li, Kong, Zhuang, Chen, and Zhang, "TPD: Enhancing Student Language Model Reasoning via Principle Discovery and Guidance." COLM 2024.

More Selected Publications

Text-Rich Network Mining

Chen et al., "Scalable Graph Representation Learning via Locality-Sensitive Hashing." CIKM 2022.

Zhou, Jiang, Chen, Wang, "# StayHome or# Marathon? Social Media Enhanced Pandemic Surveillance on Spatial-Temporal Dynamic Graphs." CIKM 2021

Advanced Applications in Scientific Domains

Zhang*, Chen*, Jin*, Wang, Ji, Wang, Han, "A Comprehensive Survey of Scientific Large Language Models and Their Applications in Scientific Discovery." under review

Zhang, Shen, Chen, Jin, and Han, ""Why Should I Review This Paper?" Unifying Semantic, Topic, and Citation Factors for Paper-Reviewer Matching." under review.

Zhang, Jin, Chen, Shen, Zhang, Meng, and Han, "Weakly Supervised Multi-Label Classification of Full-Text Scientific Papers." KDD 2023.

Zhang, Garg, Meng, Chen, and Han, "MotifClass: Weakly Supervised Text Classification with Higher-order Metadata Information." WSDM 2022.

Zhang, Chen, Meng, and Han, "Hierarchical Metadata-Aware Document Categorization under Weak Supervision." WSDM 2021.

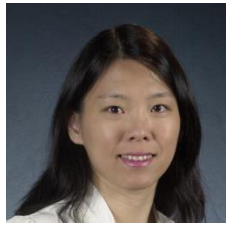
LLM for Recommendation and Retrieval

Jin, Zeng, Wang, Chen et al., "Language Models as Semantic Indexers." ICML 2024.

Hou, Li, He, Yan, Chen, McAuley, "Bridging language and items for retrieval and recommendation." arXiv 2024.

Acknowledgment

- Collaborators: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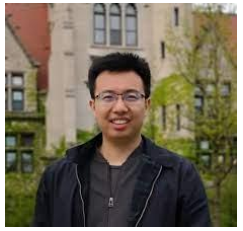
Yizhou Sun
(UCLA)


Jeff Brantingham
(UCLA)


Kai-Wei Chang
(UCLA)


Cho-Jui Hsieh
(UCLA)


Mingyan Liu
(Michigan)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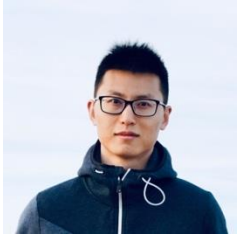
Julian McAuley
(UCSD)


Shuiwang Ji
(TAMU)


Sheng Wang
(UW)


Nitesh Chawla
(Notre Dame)


Jyun-Yu Jiang
(Amazon)


Yichao Zhou
(Google Deepmind)

- Institutions:

Thank you! Questions?

Xiusi Chen

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