

Prompting is not all you need!

Or why structure and representations still matter in NLP

Mirella Lapata
School of Informatics
University of Edinburgh

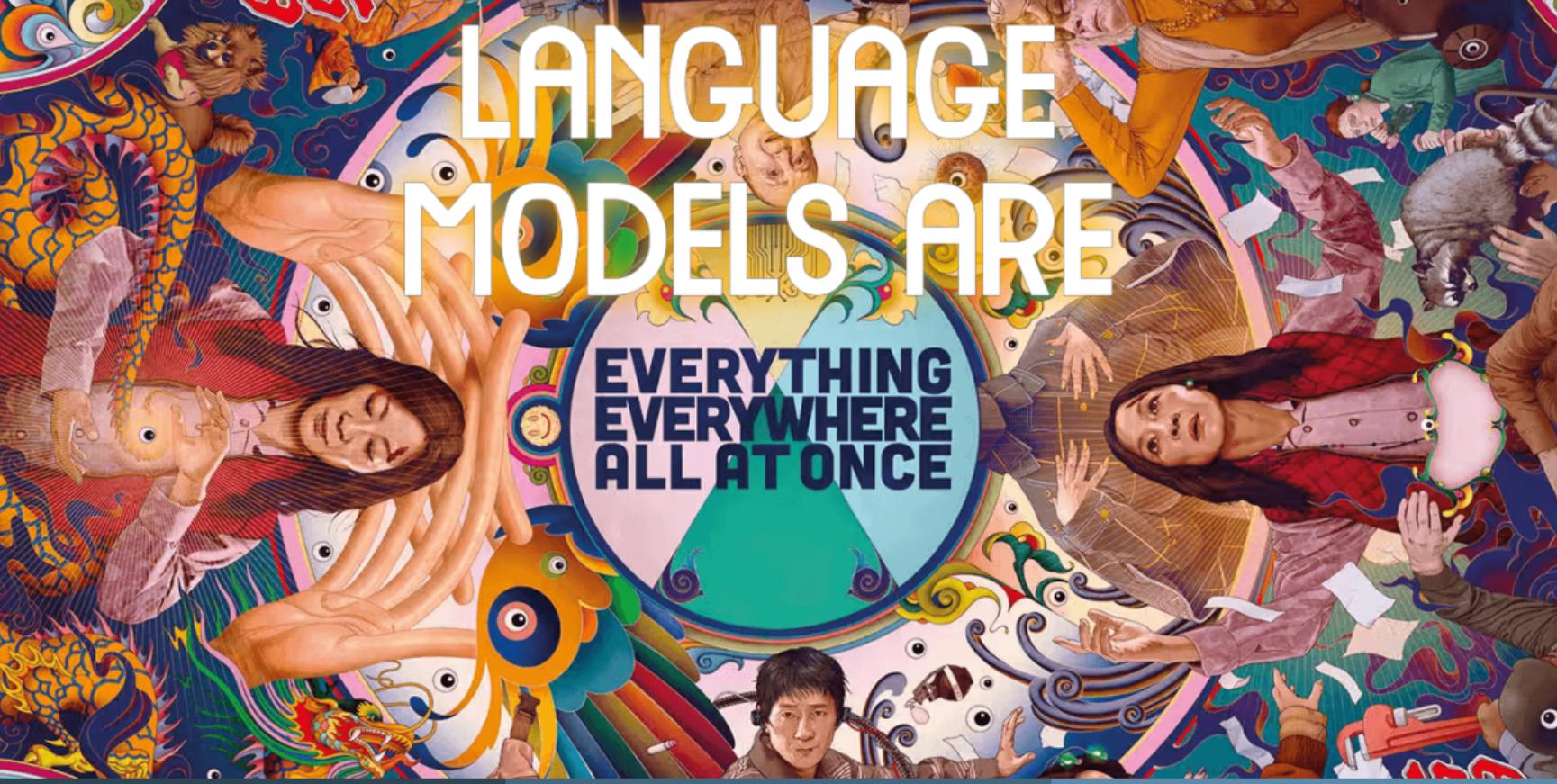


What just happened?



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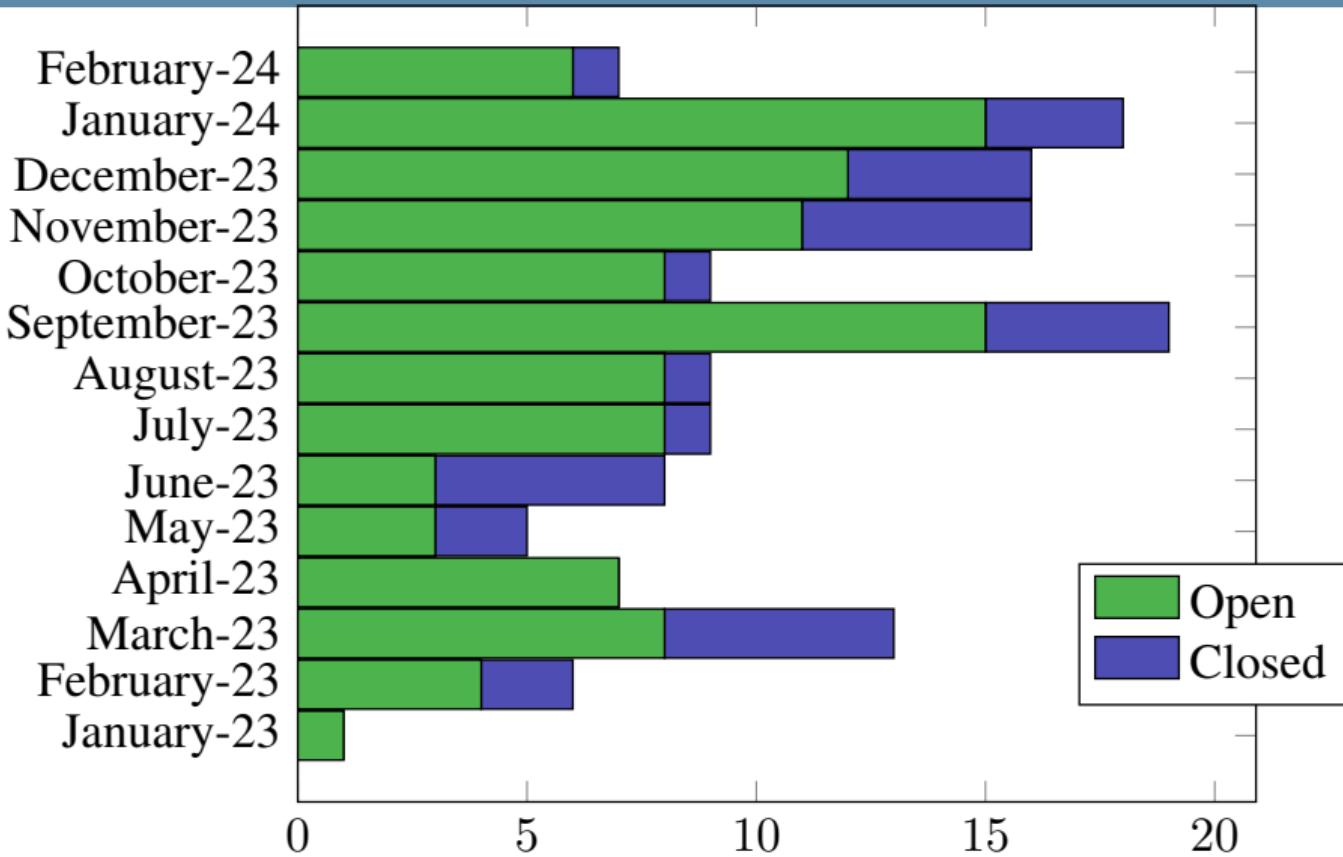
LANGUAGE MODELS ARE



EVERYTHING
EVERYWHERE
ALL AT ONCE

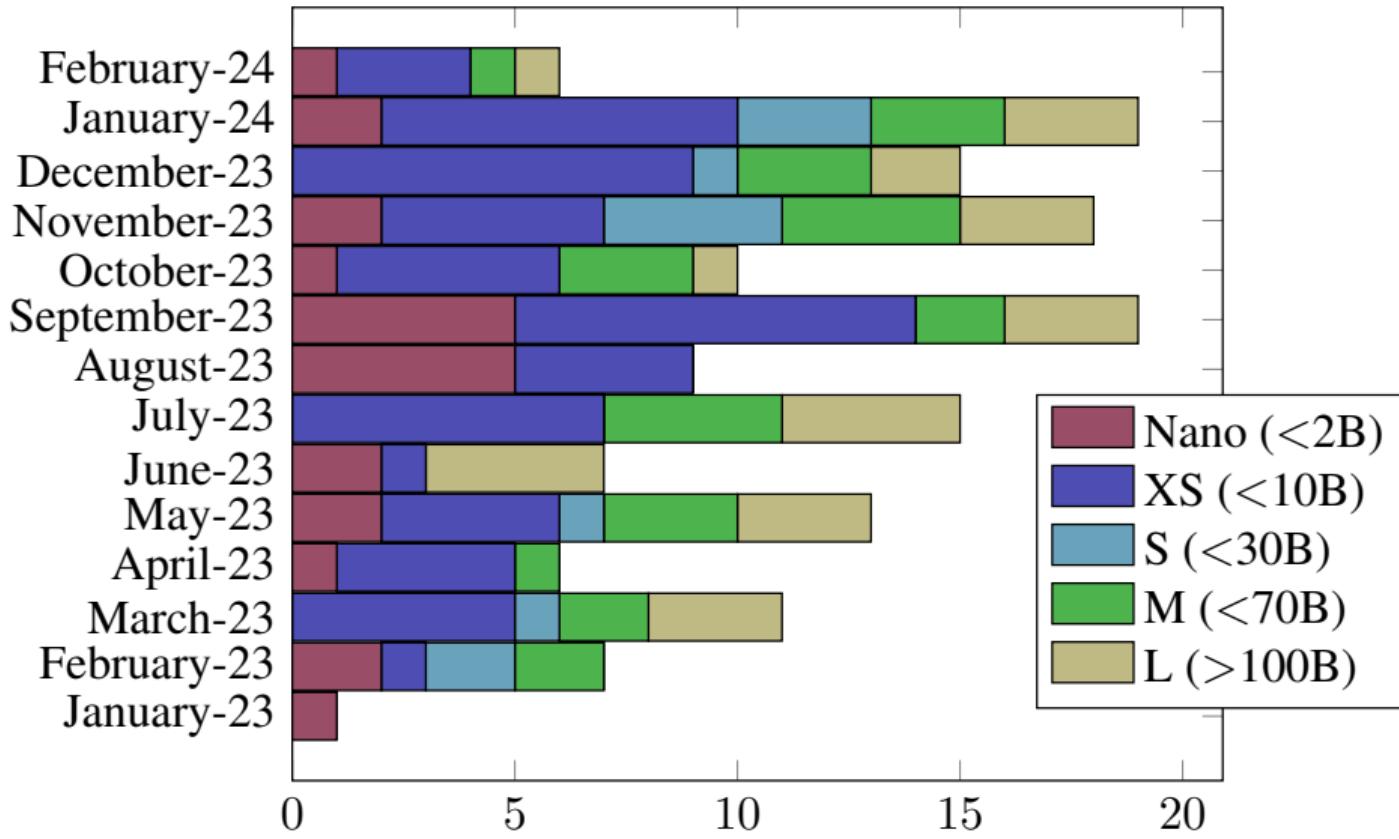
Spoiled for choice

Source: <https://lifearchitect.ai/models/>



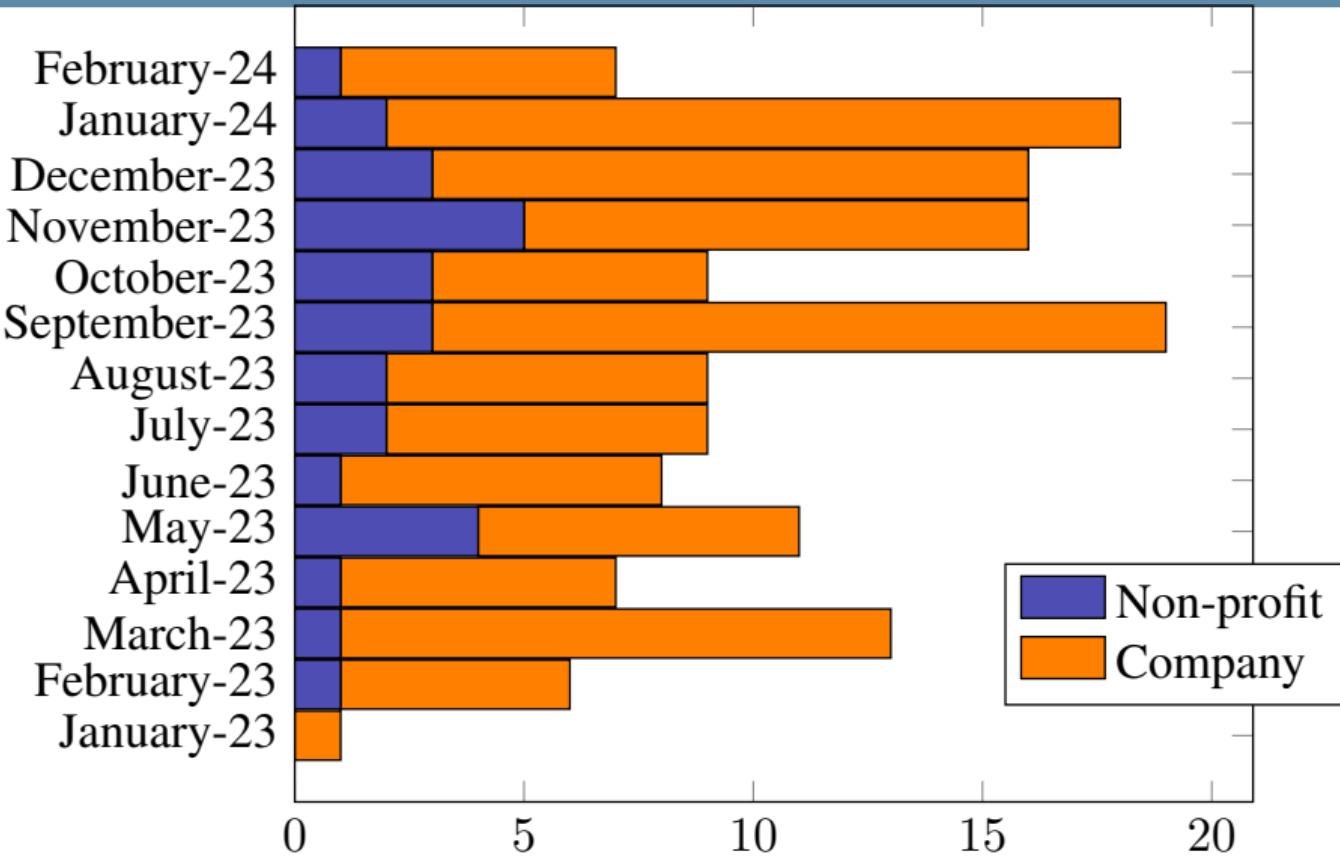
How big are these LLMs?

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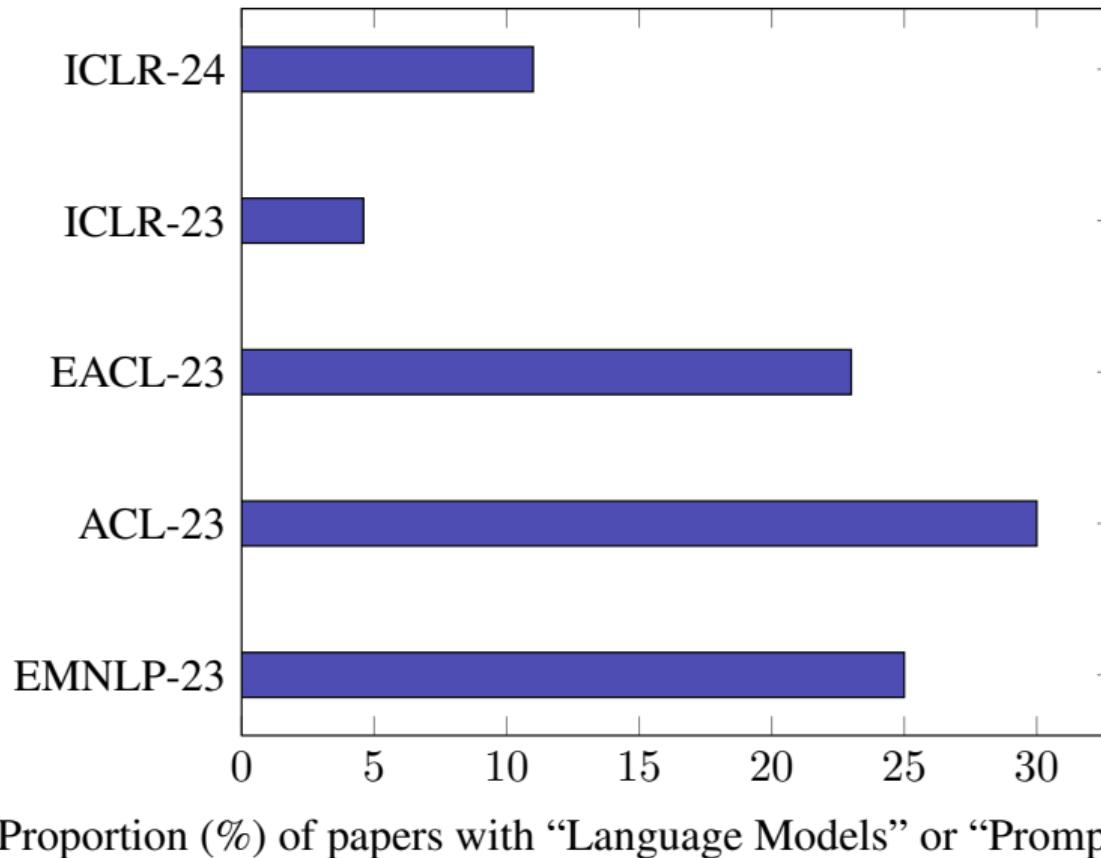


Who builds LLMs?

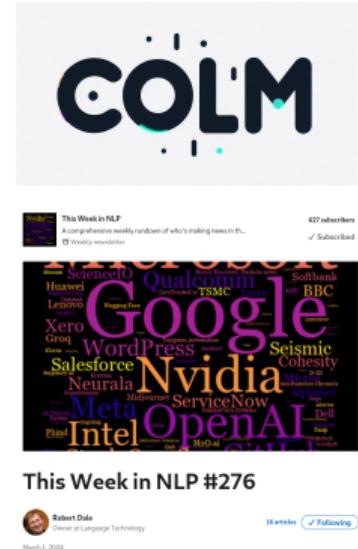
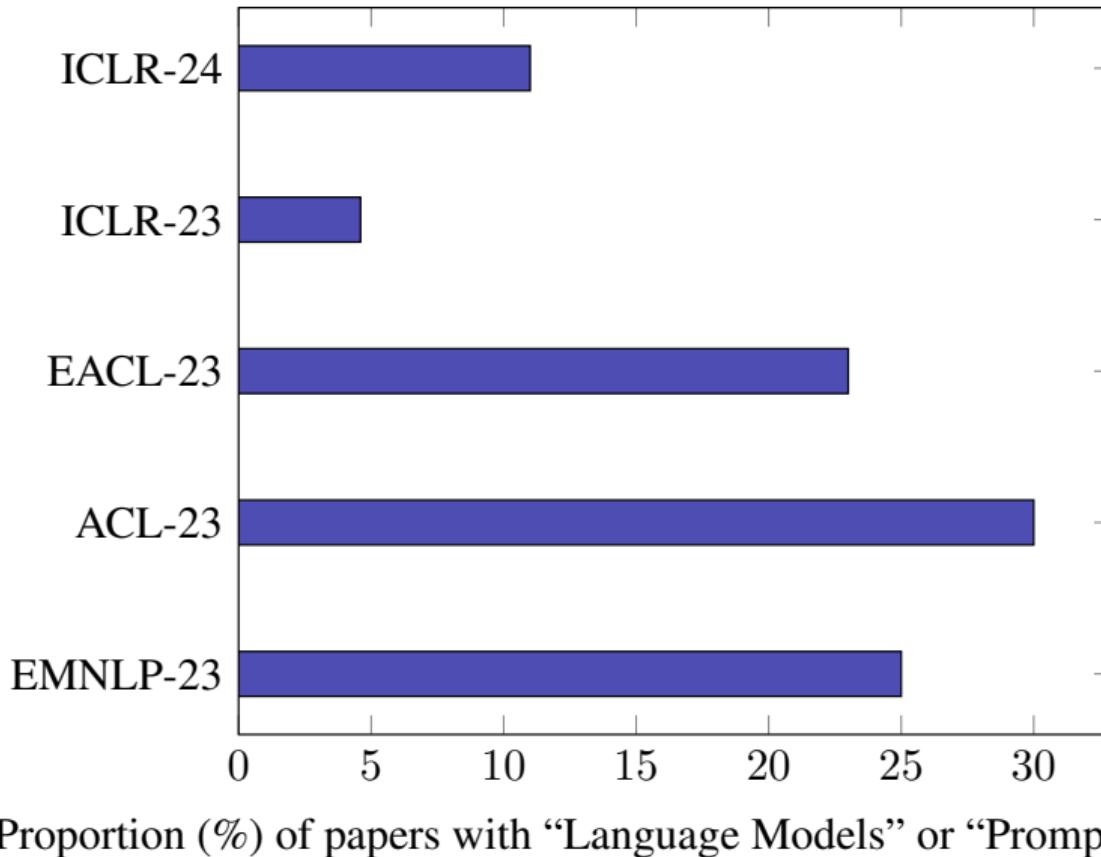
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Research on LLMs



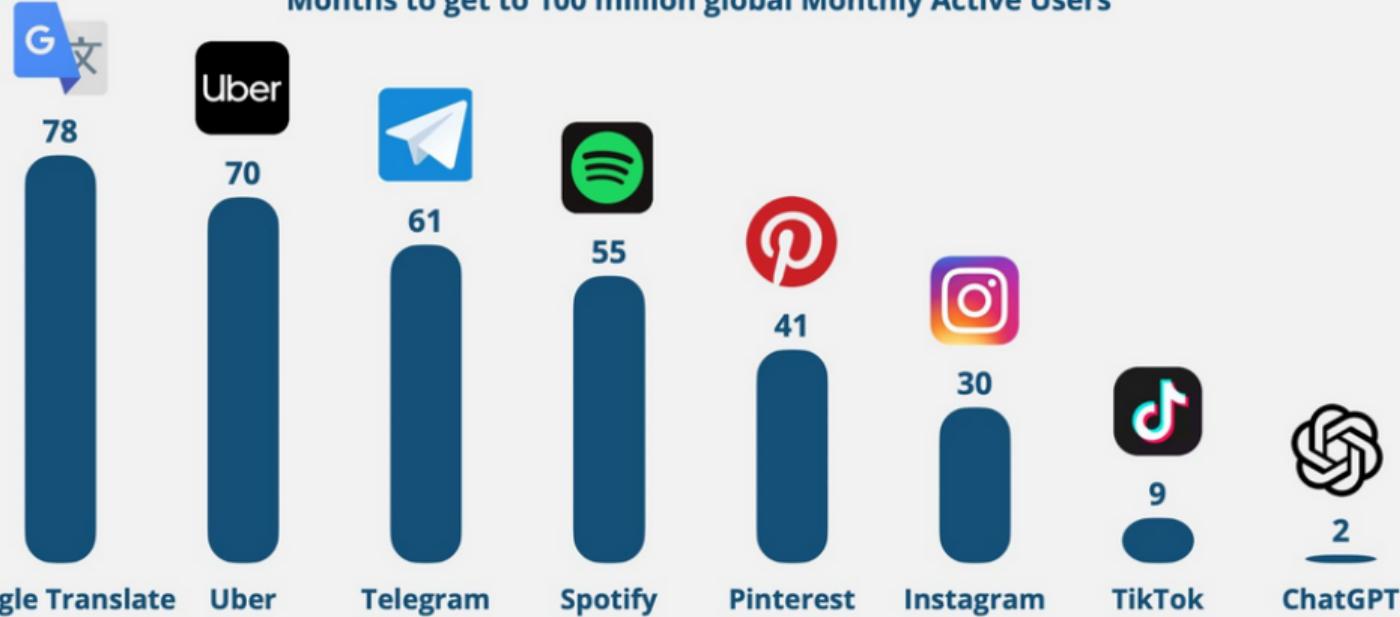
Research on LLMs



Users are keen

Time to Reach 100M Users

Months to get to 100 million global Monthly Active Users

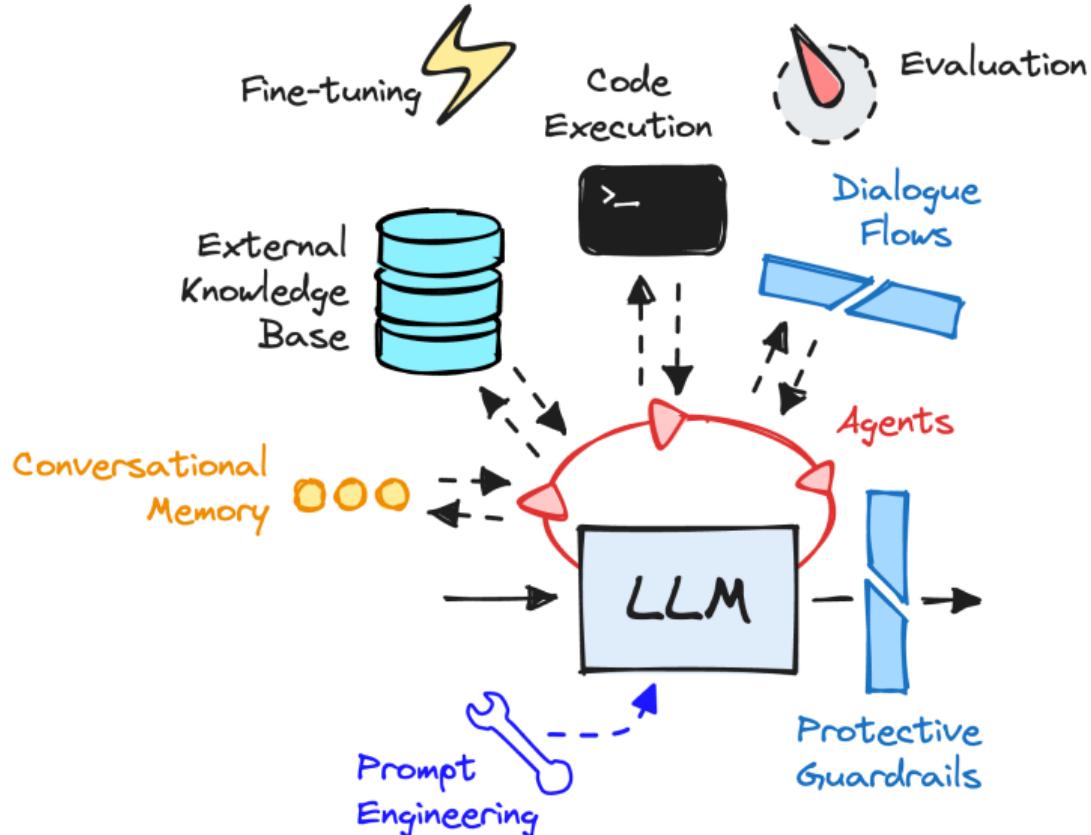


Source: UBS / Yahoo Finance

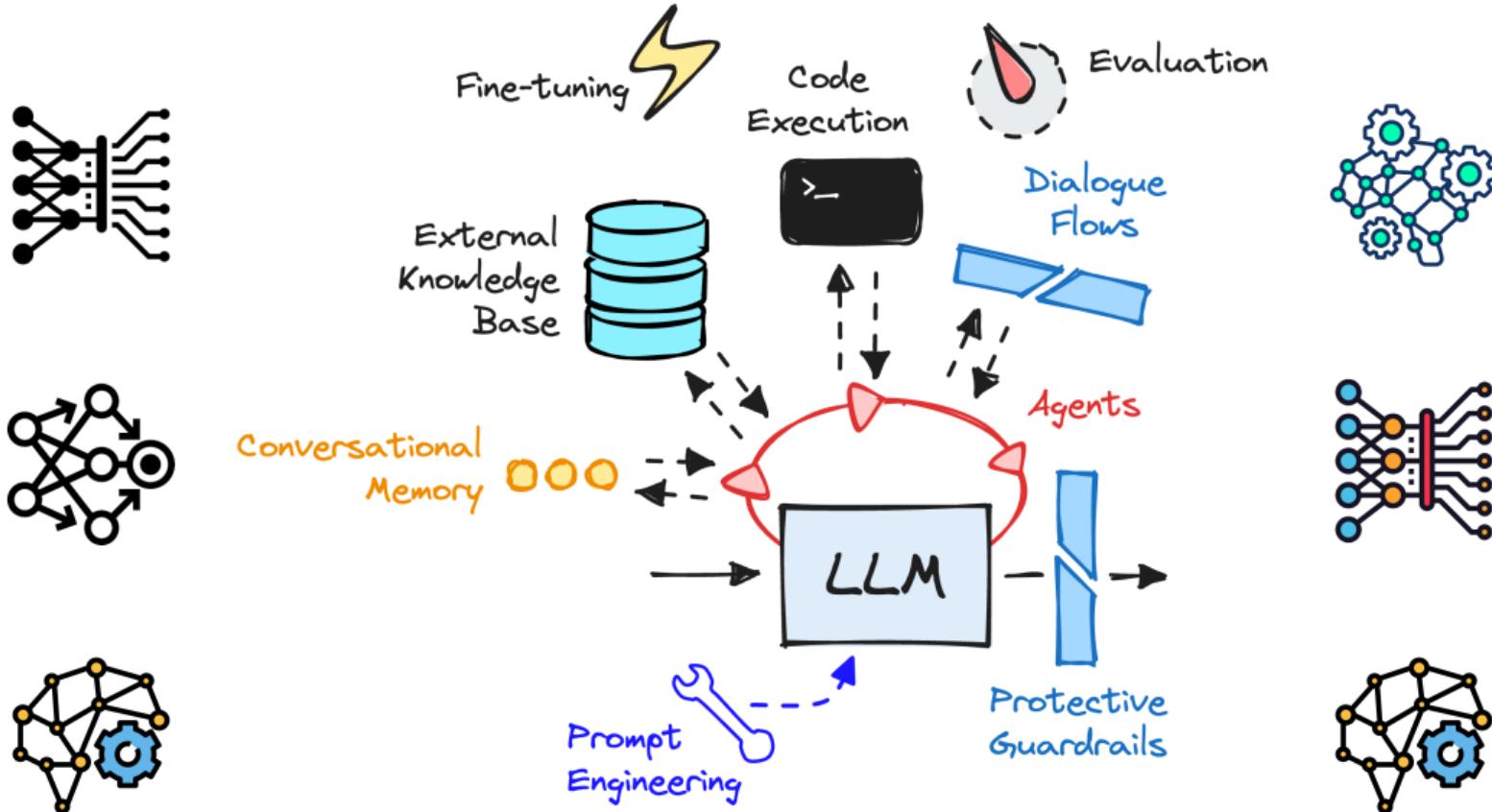
@EconomyApp

APP ECONOMY INSIGHTS

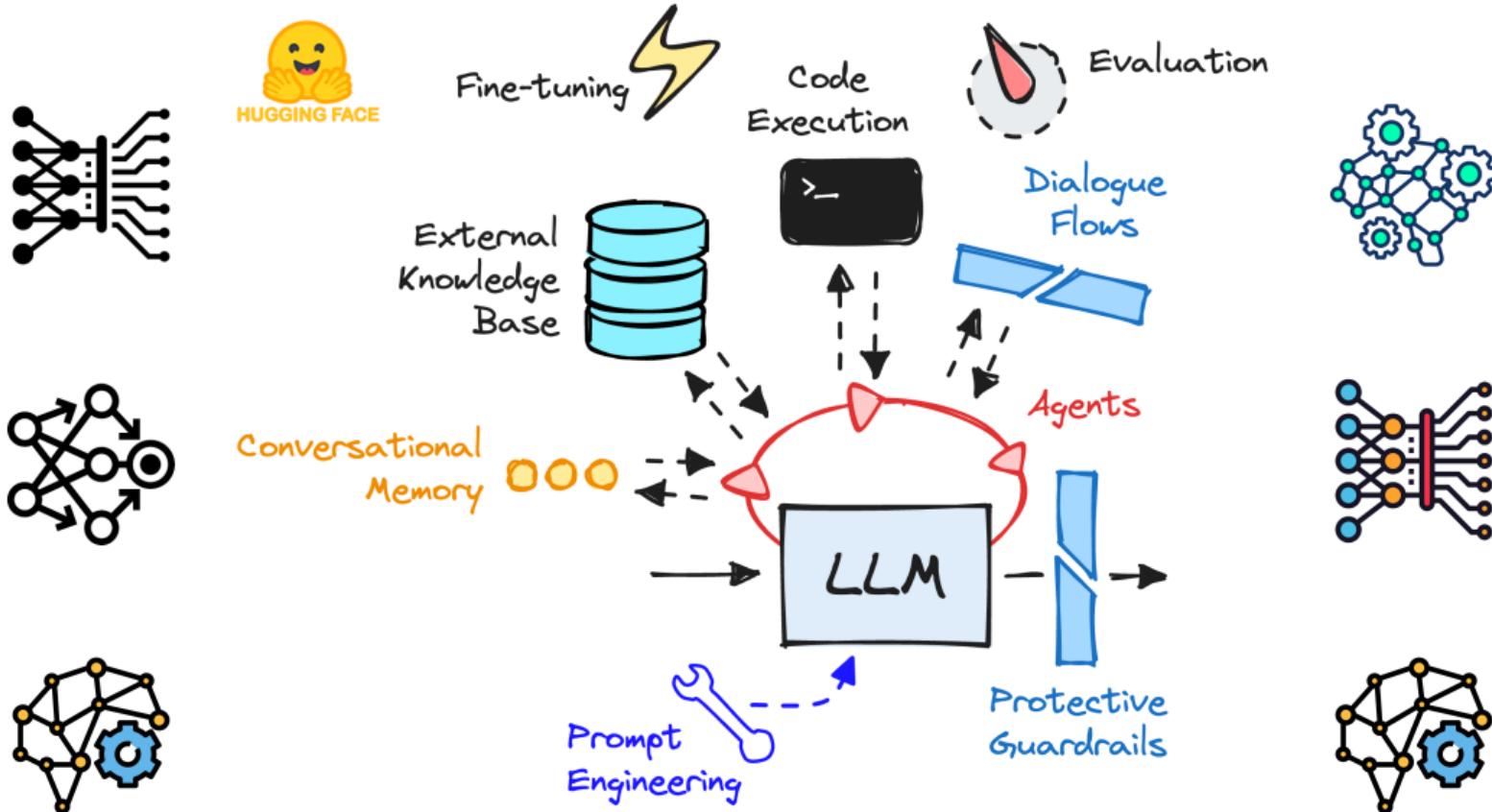
There is more to NLP than LLMs!



There is more to NLP than LLMs!



There is more to NLP than LLMs!



The NLP Ecosystem



generated by dall-e-2

I am not the only one talking about modules!



Jacob Andreas, Marcus Rohrbach, Trevor Darrell, and Dan Klein. 2016.
Neural module networks. CVPR 2016.



Colin Raffel, Build an Ecosystem, Not a Monolith at Simons Institute
Workshop on Large Language Models and Transformers, 2023.



Modular Deep Learning, Jonas Pfeiffer, Sebastian Ruder, Ivan Vulić,
Edoardo Maria Ponti, TMLR 2023.



Toolformer: Language Models Can Teach Themselves to Use Tools
Timo Schick, Jane Dwivedi-Yu, Roberto Dessì, Roberta Raileanu, Maria
Lomeli, Eric Hambro, Luke Zettlemoyer, Nicola Cancedda, Thomas
Scialom. arxiv, 2023.

The NLP Ecosystem (in practice)

The real voyage of discovery consists not in seeking new landscapes, but in having new eyes. **Marcel Proust**



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- Structure in problem decomposition

The real voyage of discovery consists not in seeking new landscapes, but in having new eyes. **Marcel Proust**



- Structure in problem decomposition
- Structure in representation space

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- Structure in space and problem decomposition

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Part I

Summarization of TV Shows

How about a soap opera?



love him, she takes her things and leaves. **Bridget** and **Dante** are at home discussing **Stephanie**'s interference in the custody of **Dino**. **Bridget** suggests that perhaps **Eric** can help them. **Dante** worries about what losing his job would do to his work visa. **Bridget** convinces him that because they all love **Dino**, they should be able to work something out. After some wine, **Bridget** reveals that she is ready to make love with **Dante**. As the two were in bed, **Dante** stops and reaches in the bedside drawer and presents **Bridget** with an engagement ring and pops the question. **Brooke** goes to see **Nick** at his office and tells him that she has left Forrester. **Nick** is pleased, although **Brooke** confesses that she hurt **Ridge** badly by walking out. **Nick** whisks her off to the Marone jet for a surprise getaway! At Forrester, **Ridge** angrily accuses **Stephanie** of causing all his problems with **Brooke**. **Stephanie** is stunned as **Ridge** bashes her with a vengeance and then clutching his chest, collapses to the floor!

Ridge continues to beg **Brooke** to reconsider her decision to leave Forrester as **Stephanie** continues to voice her opinion. At Marone, **Taylor** pays **Nick** a visit. **Nick** is still angry about what **Taylor** implied when she disclosed that **Brooke** and **Ridge** slept together. **Taylor** tries to apologize and asks if things are all right between **Nick** and **Brooke**. **Nick** tells her that everything is fine and **Brooke** is quitting her job at Forrester. **Taylor** is unconvinced that **Brooke** will be able to let go of either Forrester or **Ridge**! **Brooke** tells **Ridge** that she cannot fight with **Stephanie** any longer and that her future is with **Nick**. After kissing **Ridge** and saying that a part of her will always

The summarization task is extremely challenging

An instance of **dialogue summarization**

- **Long input:** ~60 minute videos, ~5,700 tokens

Papalampidi and Lapata (2023, EACL), Mahon and Lapata (2024, arxiv)

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An instance of **dialogue summarization**

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- **Long input:** ~60 minute videos, ~5,700 tokens
- **Complex semantics:** long-range dependencies
- **Different input sources:** video + language + audio
- **Data scarcity:** difficulty with collection and annotation
- **Evaluation:** how can we know the model generated a good summary?

Papalampidi and Lapata (2023, EACL), Mahon and Lapata (2024, arxiv)

SummScreen^{3D} based on SummScreen (Chen et al., 2022)

Transcript (dialogue)

Lucy: To our party.
Jamal: Good job, case.
Casey: Big boss never said that I couldn't change a vampire's life.
Jamal: That's right.
Lucy: How's it coming, cuz?
Rafe: Don't bother trying to move, all right? These are 100% vampire cuffs.
Jamal: I got him, I got him.
Caz: Ugh! You little --
Rafe: Shut up! Keep him quiet.
[Noise]
Lucy: Hey, hey, hey. Somebody's coming. Someone's coming.
Rafe: Over there.
Alison: Hey, Lucy. Rafe! You guys -- hey. Lucy, she's coming. Reese --
Rafe: All right, over here, ok. Over here, come on.
Reese: Where are you, Alison? Oh. You!
Rafe: Hey, welcome to the party.
Jack: Come on --
Reese: Oh, Jack, it's a trap! Go! Go! Go! Go!
Lucy: Not so fast.
Jack: Lucy -- Lucy, Rafe, what's going on here, huh?

Full-length video



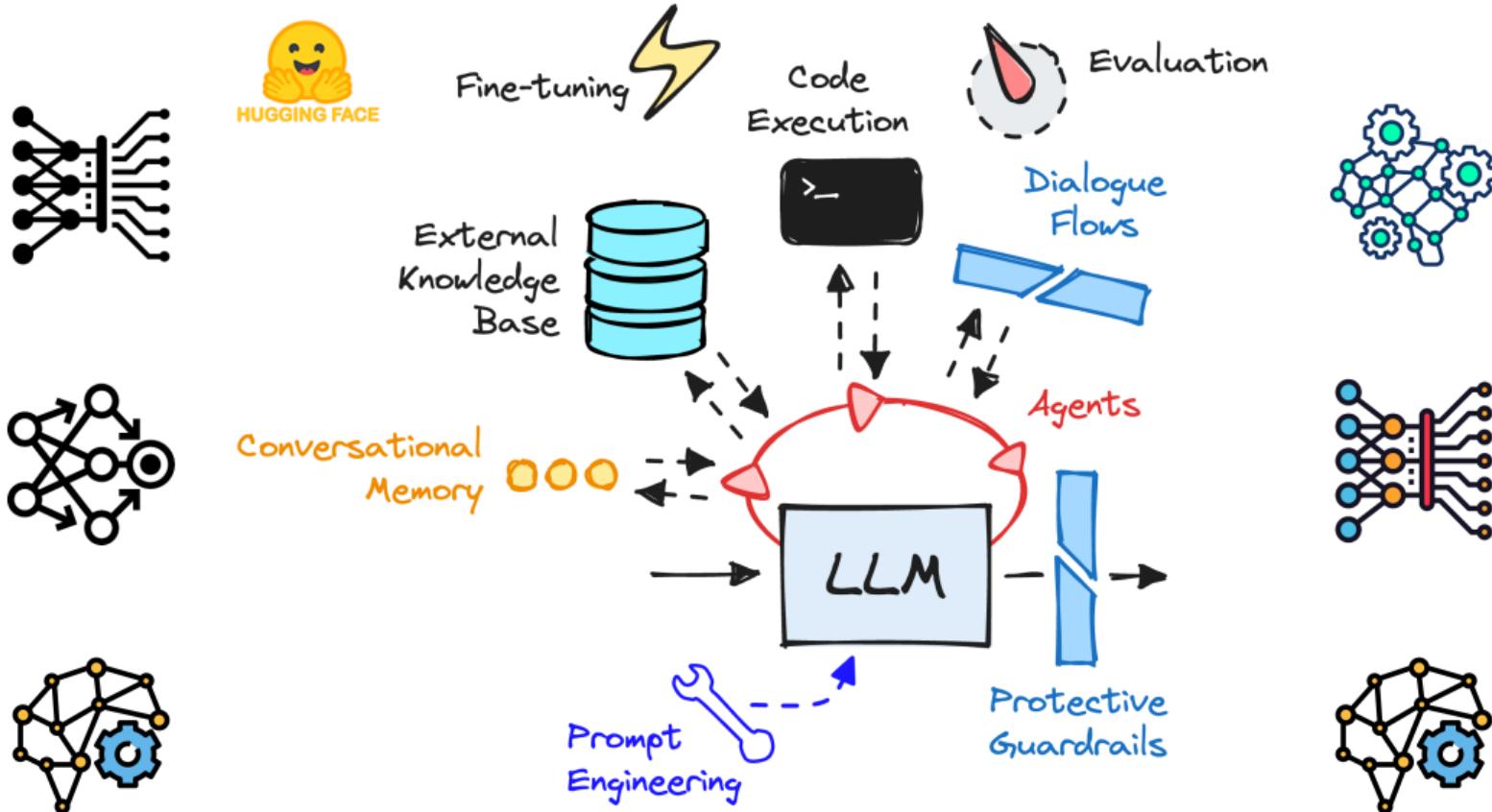
Port Charles The



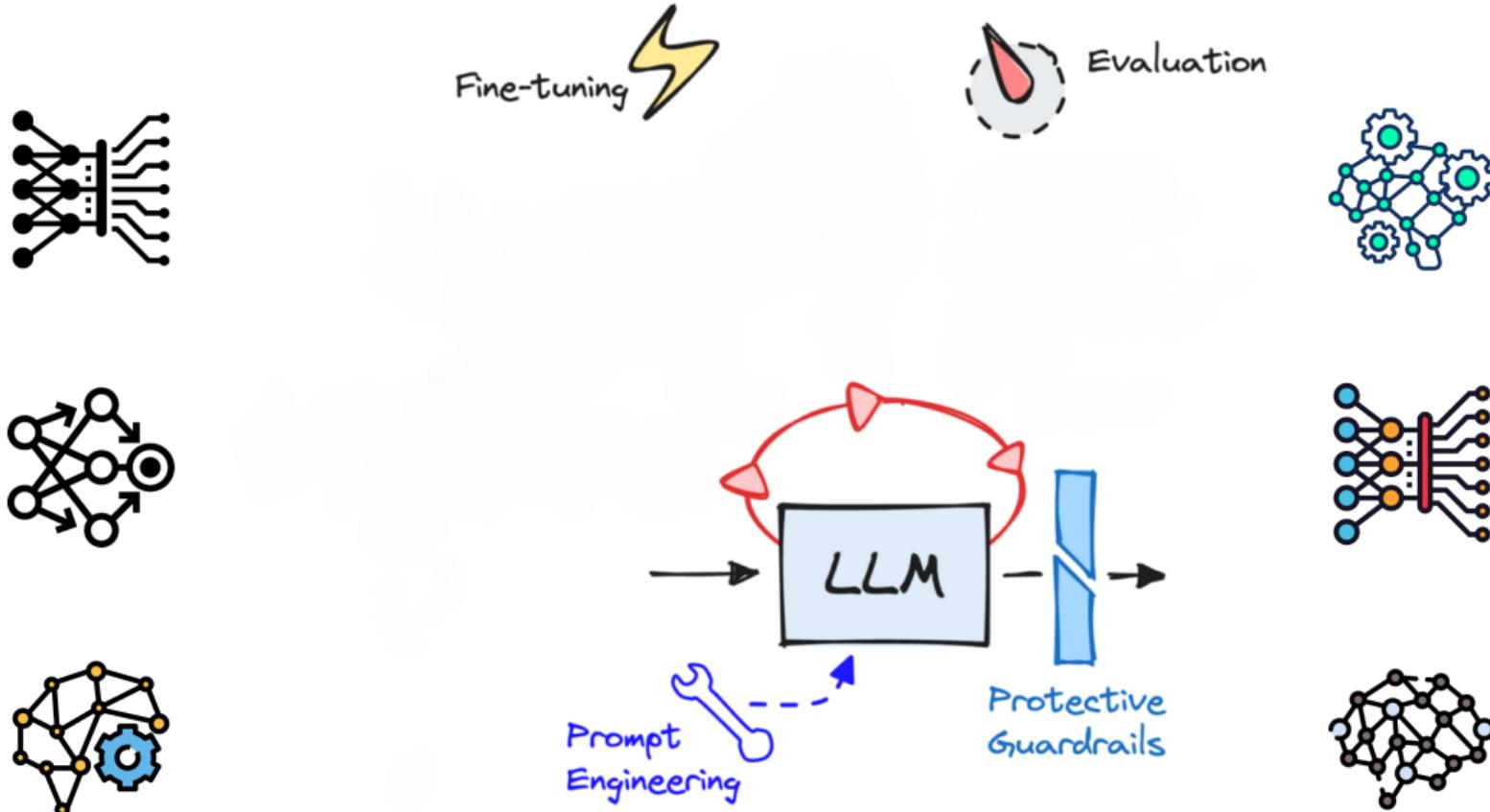
Summary

Kevin is freed by Karen, who drops by the lighthouse. Rafe and Lucy try to persuade Ian to save himself by killing Joshua, but he refuses to even consider it. Alison provokes Reese into chasing her to the healing pool, and Casey lures Caz there on the pretense of going to a party. After breaking into the studio, Ian learns that Joshua is planning to blow up the hot spring. Jamal helps Rafe and Lucy at the healing pool. As Ian prepares to grab Joshua, Kevin injects something into his neck. Caz willingly jumps into the healing pool. Jack attempts to rescue Reese, who tries again to bite Alison but can't. Kevin begins to build a thick wall to seal Ian inside. Rafe throws Reese into the water. Caleb senses that something is wrong with his "family."

There is more to NLP than LLMs!



There is more to NLP than LLMs!



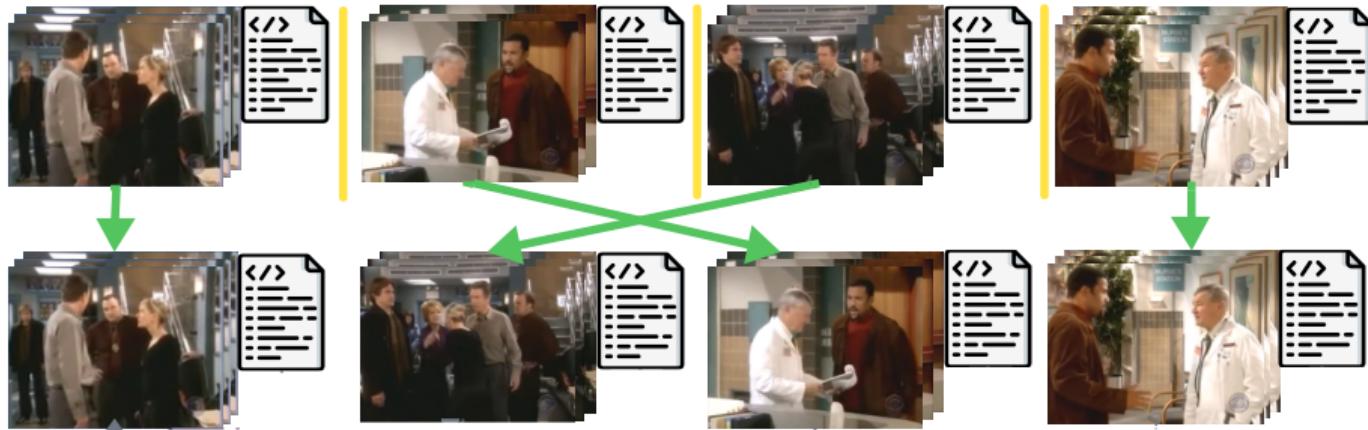
Structure in video summarization



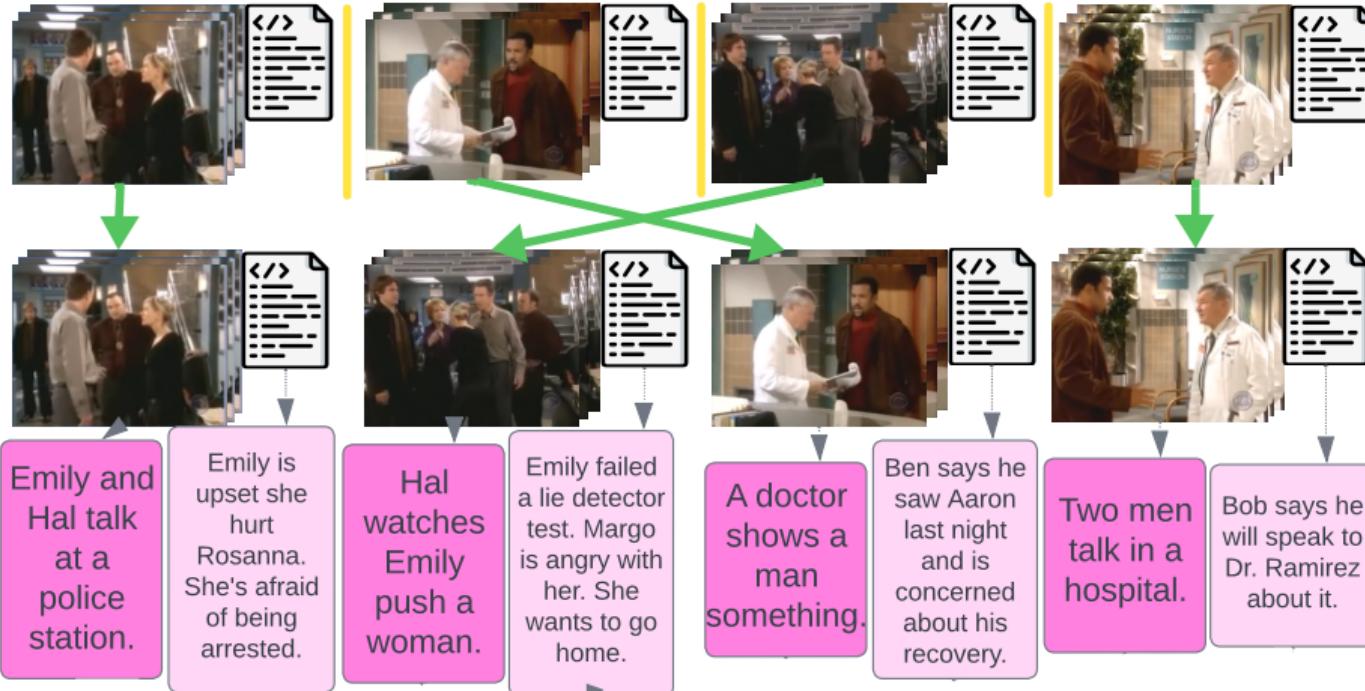
Structure in video summarization



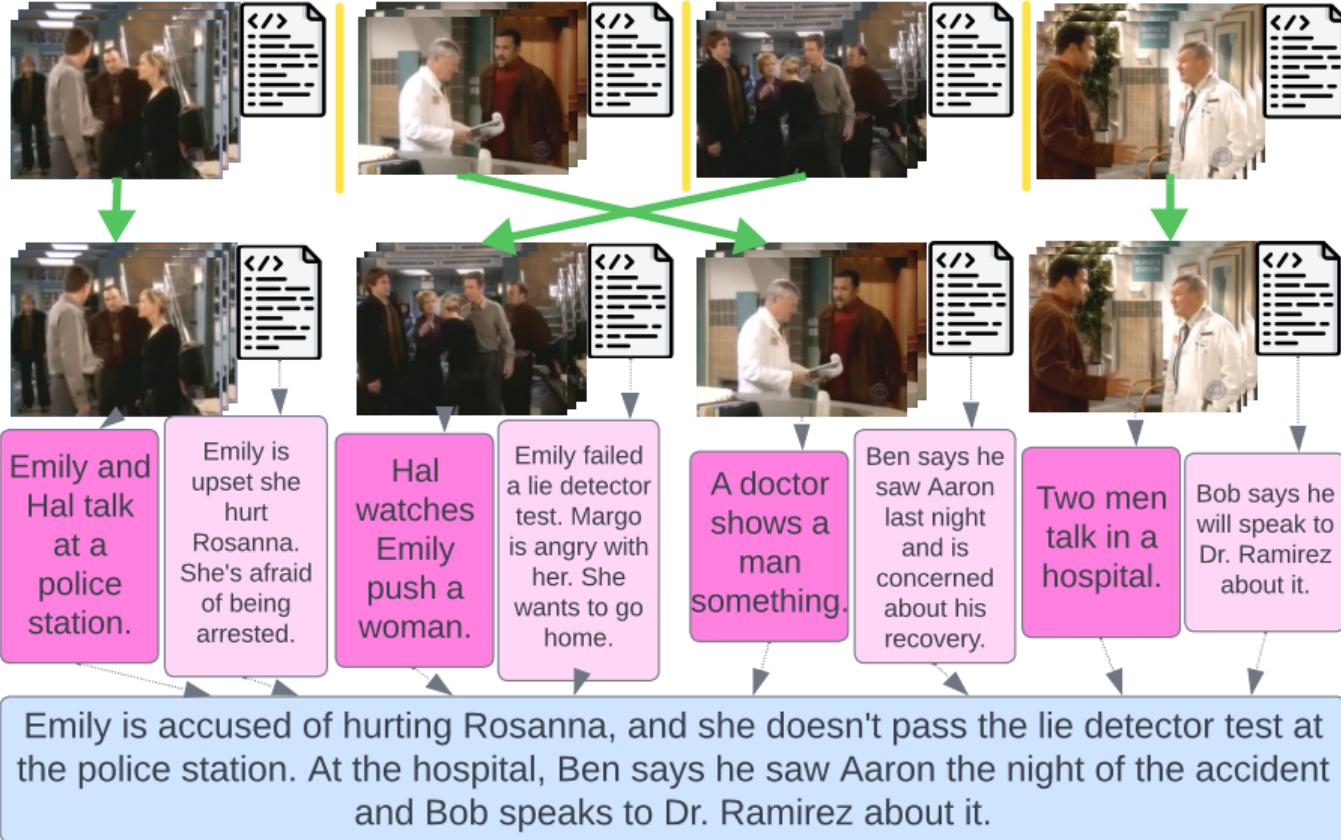
Structure in video summarization



Structure in video summarization



Structure in video summarization



How do we automatically evaluate the summaries?

- ROUGE does not discriminate between different types of errors, in particular those relating to factuality (Min et al., 2023; Clark et al., 2023).
- LLM outputs are now preferred to human-written references (Zhang et al., 2024; Tanya Goyal, 2022; Bhaskar et al., 2023)
- Measure fact-based precision and recall against gold summaries (Min et al., 2023).

How do we automatically evaluate the summaries?

- **Fact-precision:** are the facts in the output supported by the gold summaries?

Predicted Summary

Bridget and Dante plan to get married in Italy, but Bridget wants to spend more time with Dante. Stephanie tells Bridget that she wants to fire Dante and send him to Italy. Ridge tells Stephanie that he wants Brooke out of Forrester Creations. Brooke tells Nick that she is through fighting, she is moving to Paris. Nick tells her that she has to move out of the office.

Gold Summary

Ridge continues to beg Brooke to reconsider her decision to leave Forrester as Stephanie continues to voice her opinion. At Marone, Taylor pays Nick a visit. Nick is still angry about what Taylor implied when she disclosed that Brooke and Ridge slept together. Taylor tries to apologize and asks if things are all right between Nick and Brooke. Nick tells her that everything is fine and Brooke is quitting her job at Forrester.

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Bridget and Dante are planning to get married. Bridget wants to spend more time with Dante. They plan to get married in Italy. Stephanie wants to fire Dante. Stephanie wants to send Dante to Italy. Stephanie tells Bridget. Bridget receives the information from Stephanie. Ridge wants Brooke out of Forrester Creations. Ridge told Stephanie this. Brooke tells Nick that she is through fighting.

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Ridge begs Brooke. Brooke should reconsider her decision. Brooke decided to leave Forrester. Stephanie voices her opinion. Taylor pays Nick a visit. Nick is angry. Taylor made implications. Taylor made a disclosure. Brooke and Ridge slept together. Taylor tries to apologize. Taylor asks if things are all right between Nick and Brooke. Nick says everything is fine. Brooke is quitting her job.

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What are the modules?



Scene detection algorithm partitions transcript into contiguous chunks, cost based on MDL principle



Scene ordering algorithm minimizes the number of transitions between scenes with different speakers



Visual processing generates scenes captions with Kosmos-2 multimodal LM, 1.5B parameters



Dialogue Summarization with BART-large, 345M parameters



High-level Summarization with BART-large, 345M parameters



Evaluation, fact generation and entailment with GPT-4

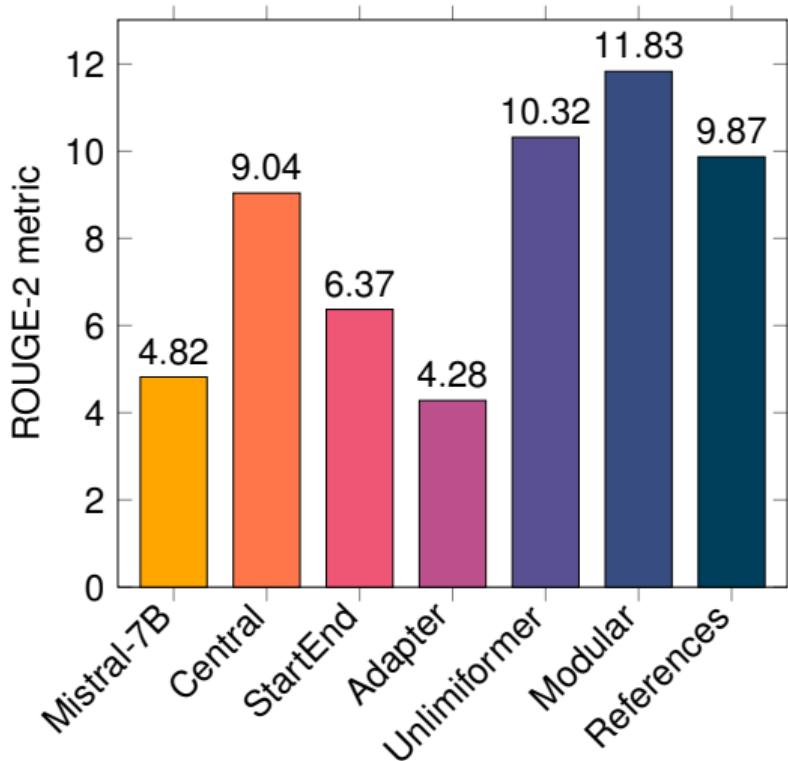


Prompt
Engineering

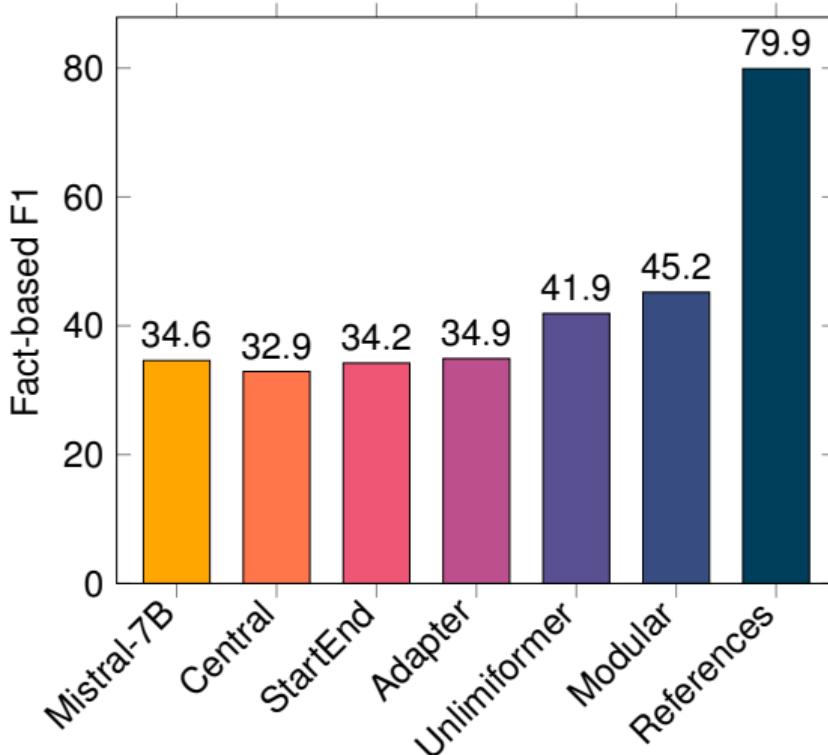
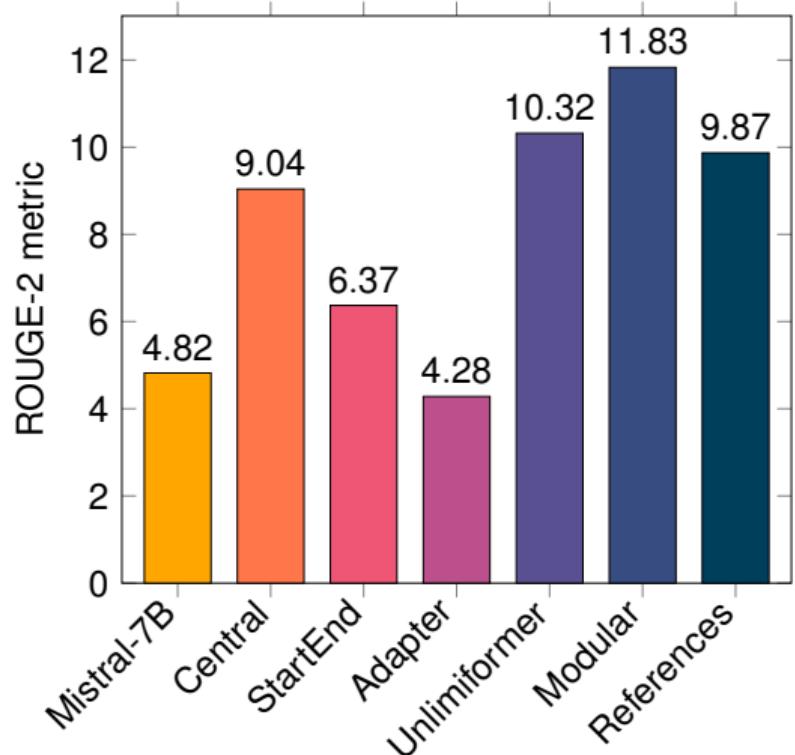


Prompt
Engineering

Results: SummScreen^{3D}



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The NLP Ecosystem (in practice)

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- Structure in representation space
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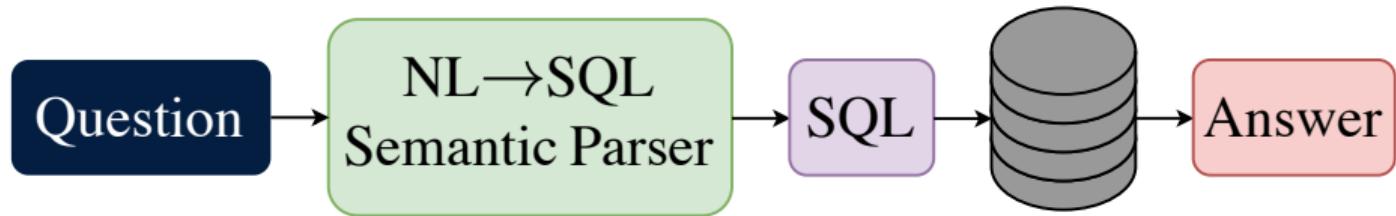
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Part II

Crosslingual Semantic Parsing

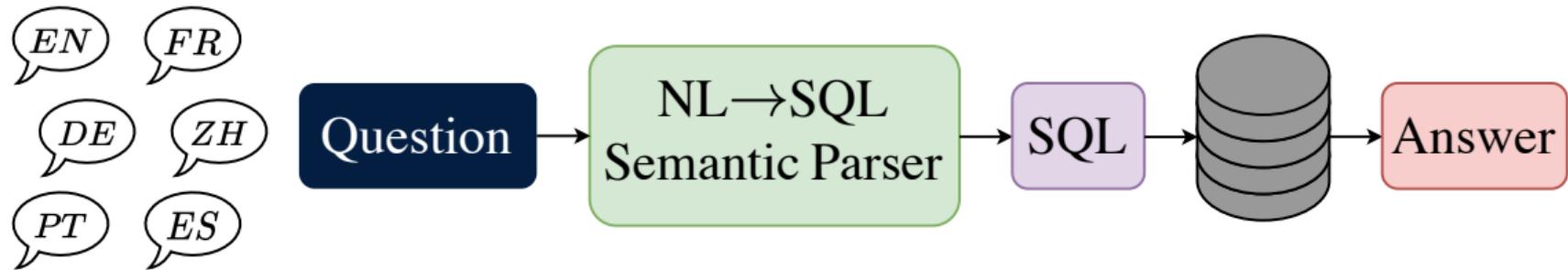
Semantic Parsing

Train a parser, p_θ , predicting programs, y , from queries, x , and a database, \mathcal{D} .



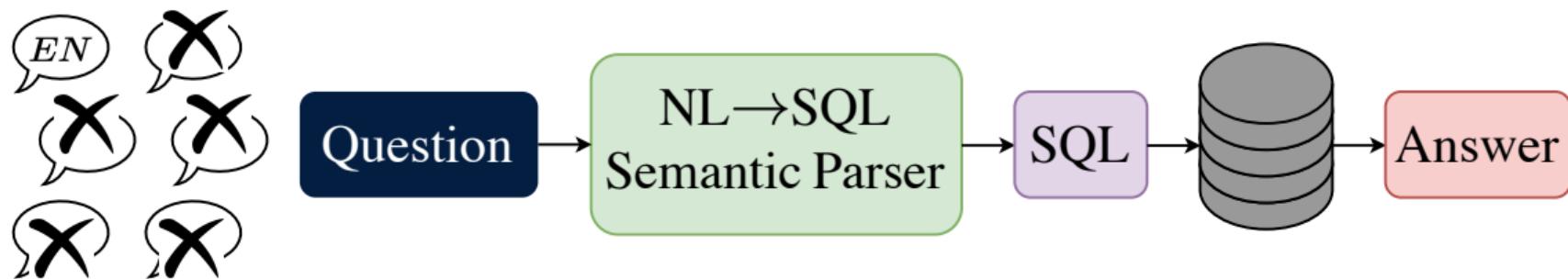
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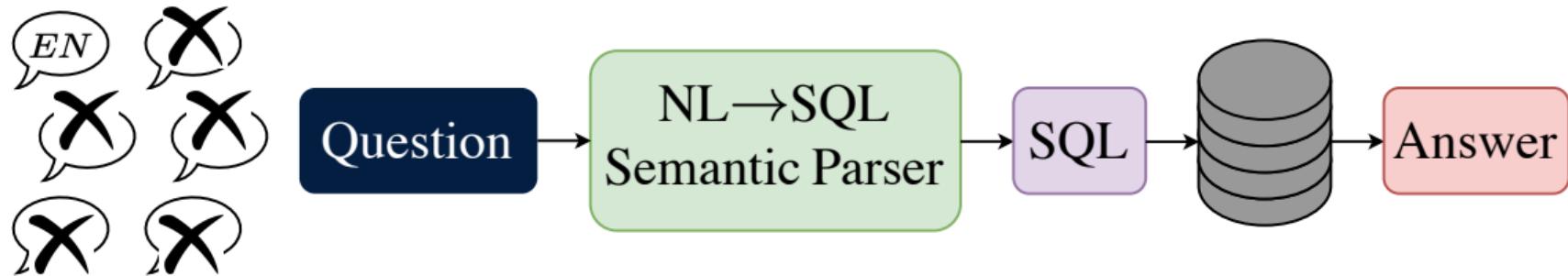
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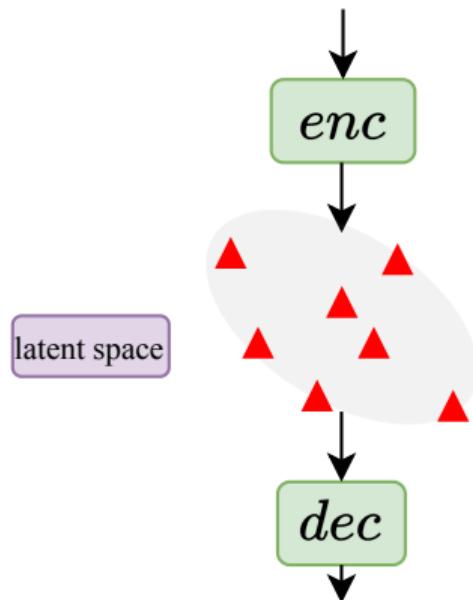


$$p_\theta(y | x_L, \mathcal{D}) \approx p_\theta(y | x_{EN}, \mathcal{D}), \text{ but } N_L \ll N_{EN}$$

LLMs cannot yet match performance of fine-tuned systems (Qiu et al., 2022; Mekala et al., 2023; Sherborne, 2024).

Semantic parsing is hard

List flights from San Francisco to Pittsburgh



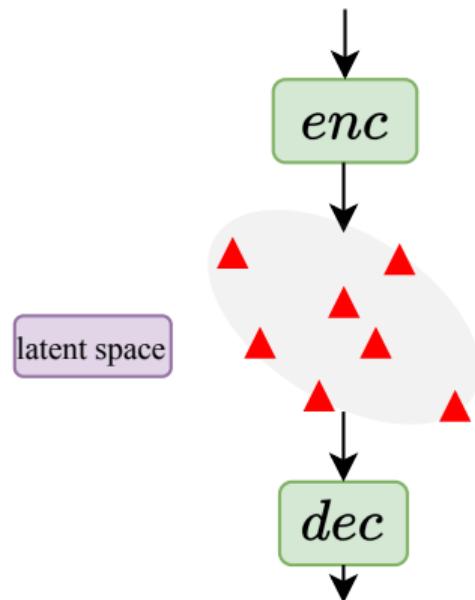
- SQL must be syntactically valid



SELECT * DISTINCT flight_1.
flight_id FROM ...

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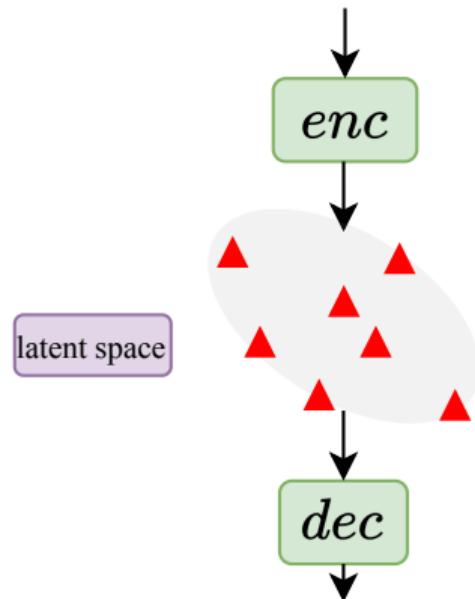


- SQL must be syntactically valid
- SQL must reflect NL semantics

✓ SELECT * DISTINCT flight_1.
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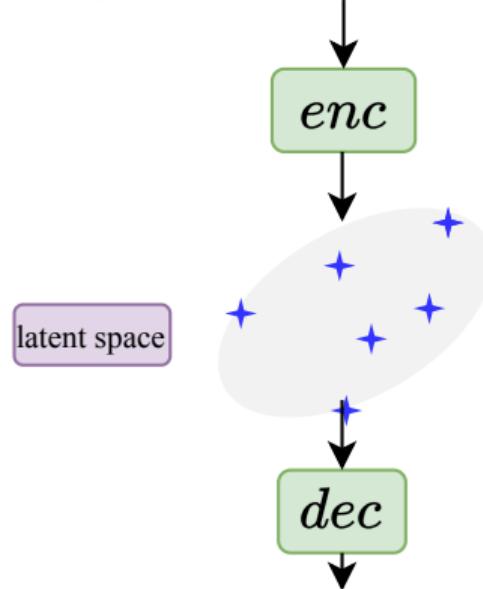
- SQL must be syntactically valid
- SQL must reflect NL semantics
- Parser must often generalize to new tables or databases



SELECT * DISTINCT flight_1.
flight_id FROM ...

Cross-lingual semantic parsing is harder

列出从 旧金山 飞往 匹兹堡 的航班



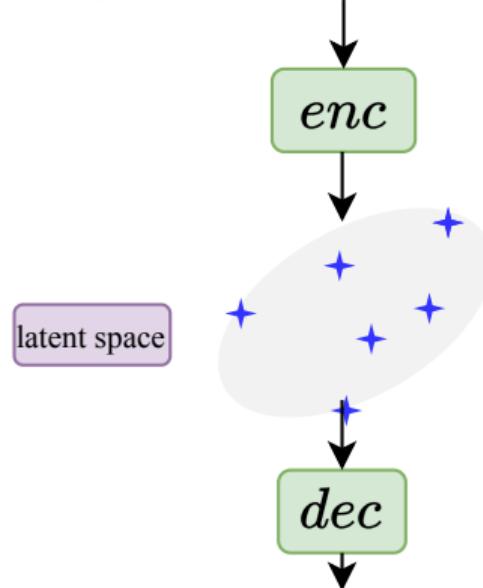
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SELECT SELECT WHERE
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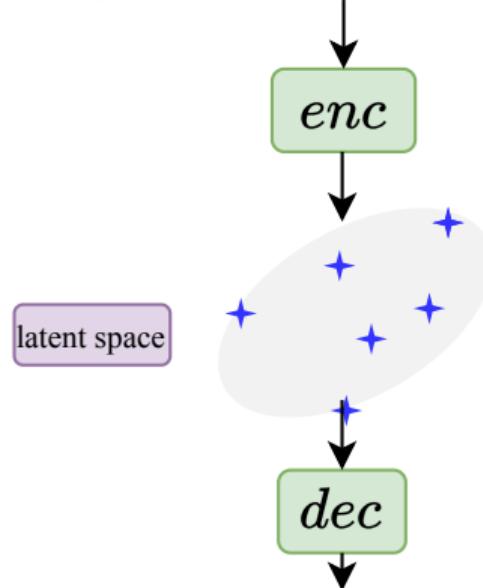
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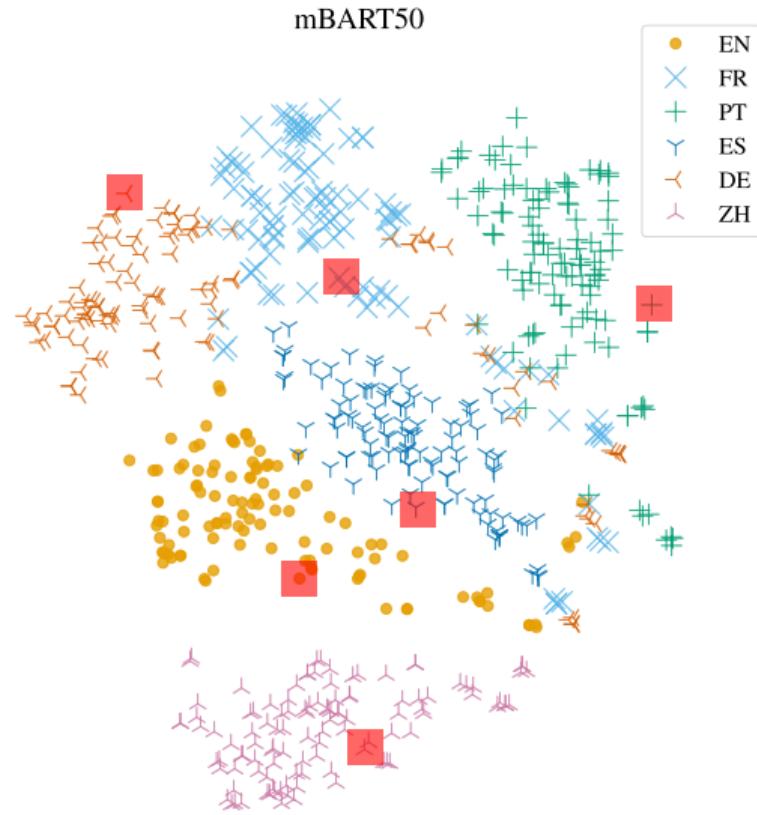
列出从 旧金山 飞往 匹兹堡 的航班



- Parser must understand questions across languages
- Complex annotation is expensive for more languages
- Multilingual learning has mixed benefit on different languages

SELECT SELECT WHERE
transport_1.airport_name IS;;;

Multilingual Modeling is also hard



List flights from San Francisco to Pittsburgh

Zeige mir Flüge von San Francisco nach Pittsburgh

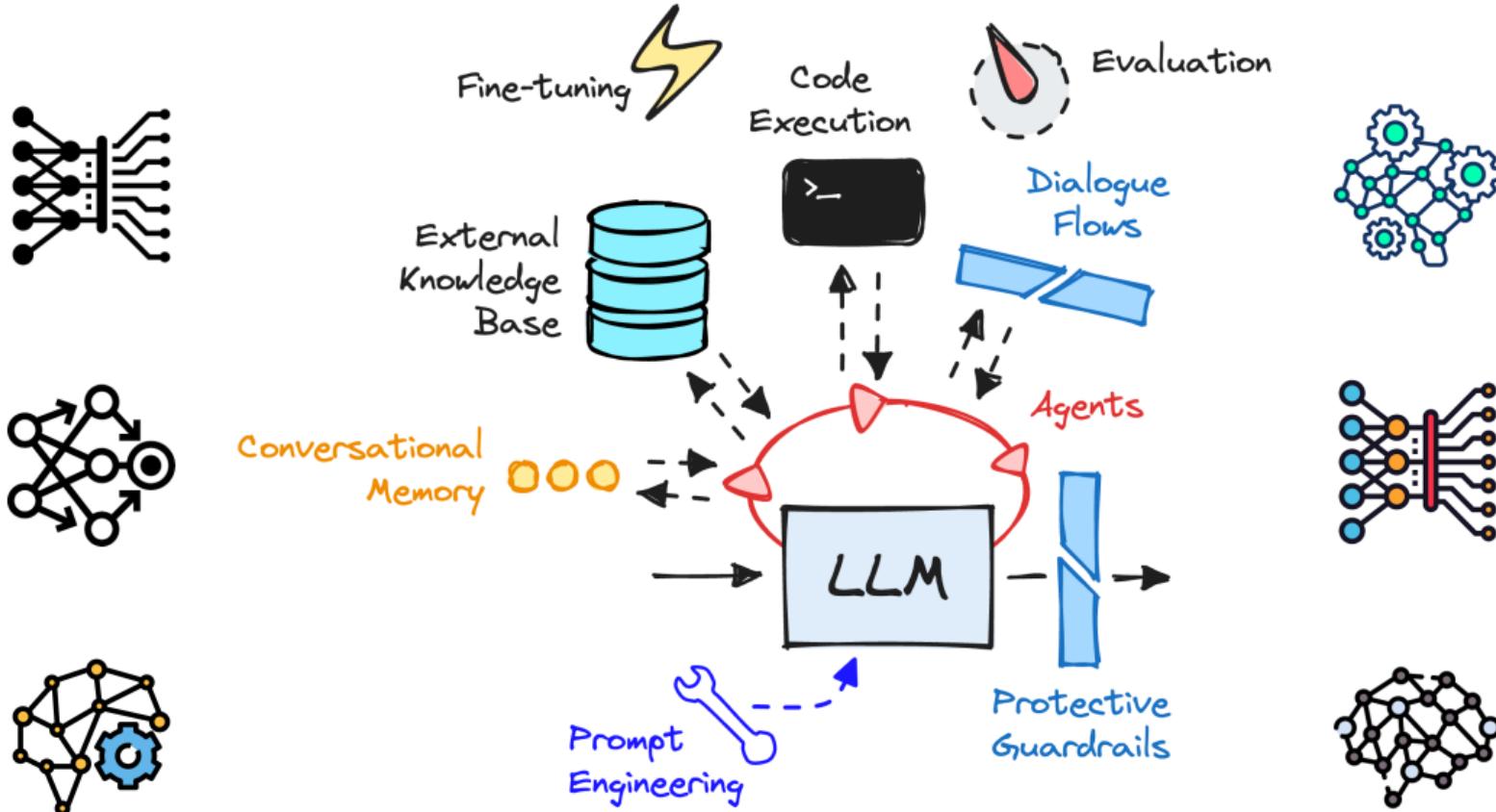
Enumera los vuelos desde San Francisco hasta Pittsburgh

Lister des vols de San Francisco à Pittsburgh.

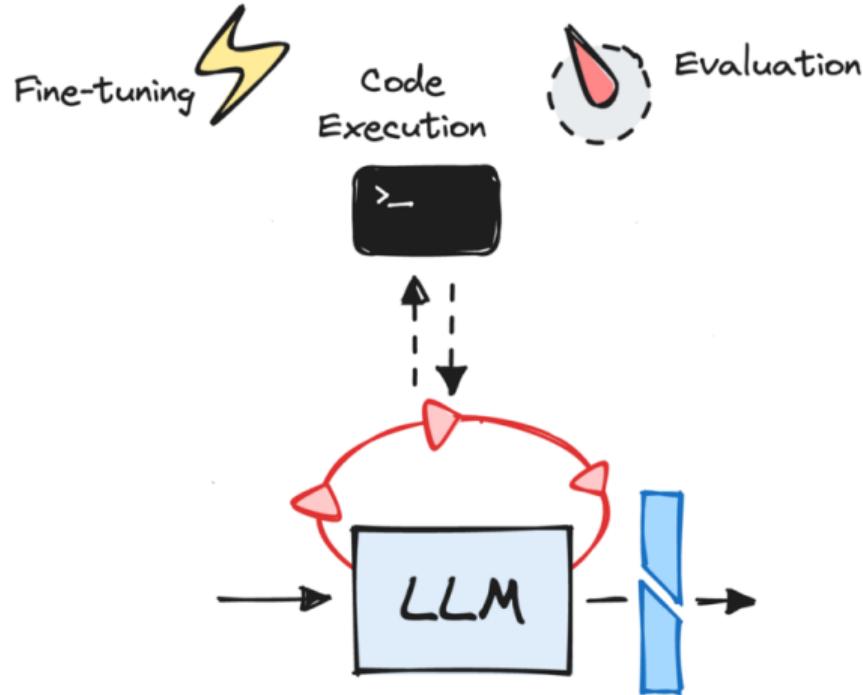
Liste voos de São Francisco para Pittsburgh.

列出从旧金山飞往匹兹堡的航班

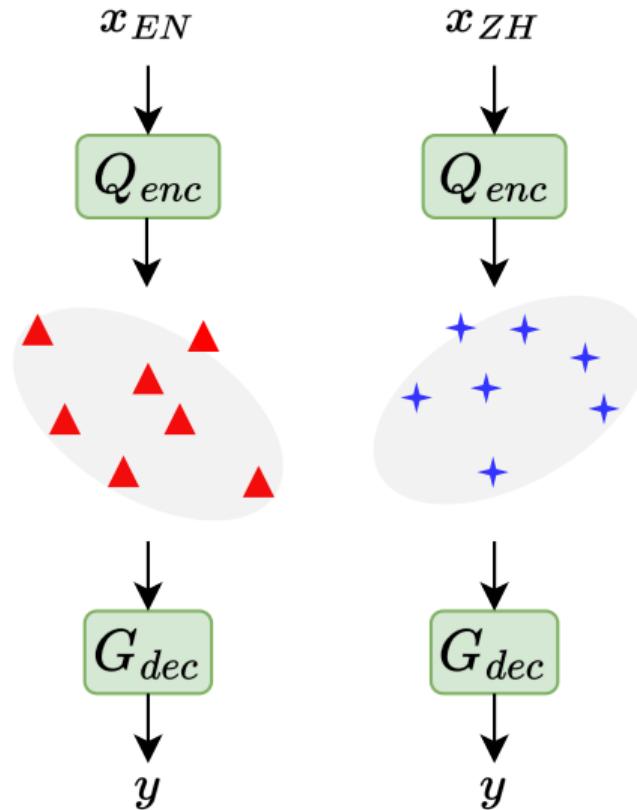
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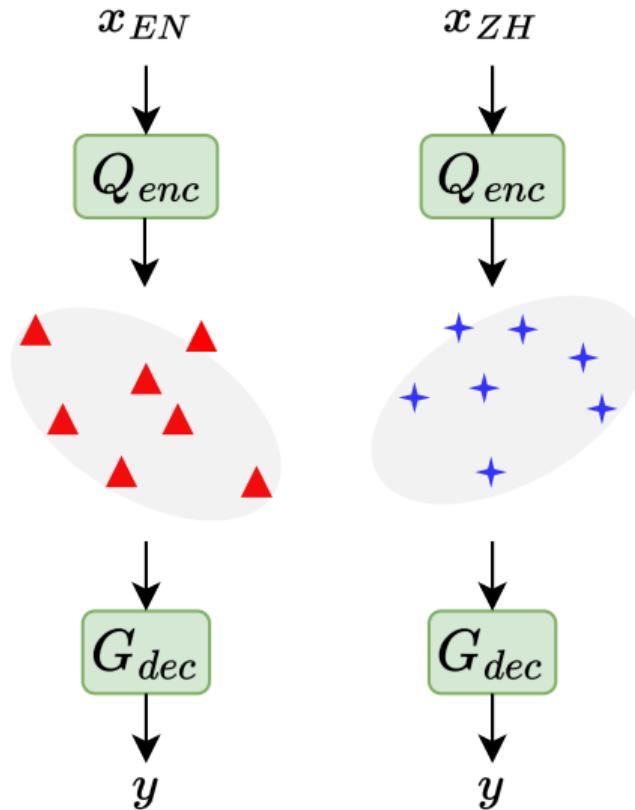


Imposing structure on latent representations



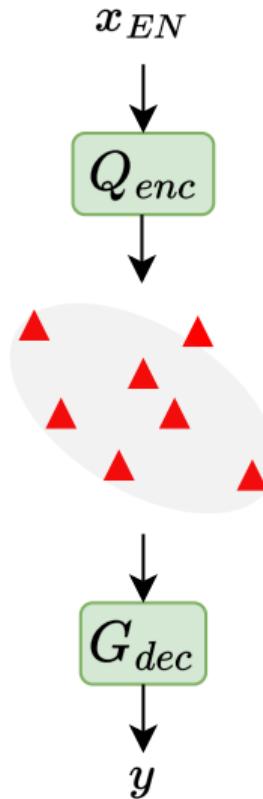
- We make the cross-lingual alignment challenge explicit using a **probabilistic latent variable Z**

Imposing structure on latent representations



- We make the cross-lingual alignment challenge explicit using a **probabilistic latent variable Z**
- We can measure and **minimize** the distance between Z samples as the distance between languages

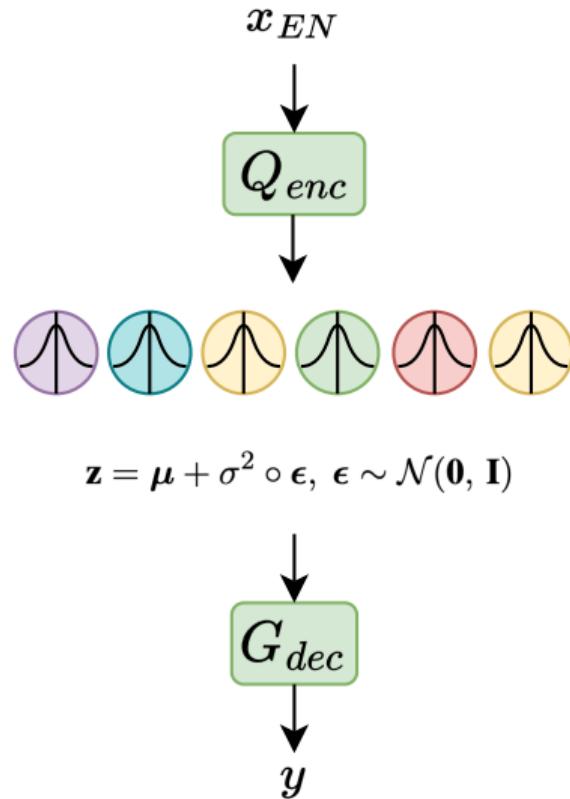
Imposing structure on latent representations



- Encoder-decoder framework has no constraints on latent space.
- The latent space is *not a distribution!*

Sherborne et al. (2023, TACL)

Imposing structure on latent representations

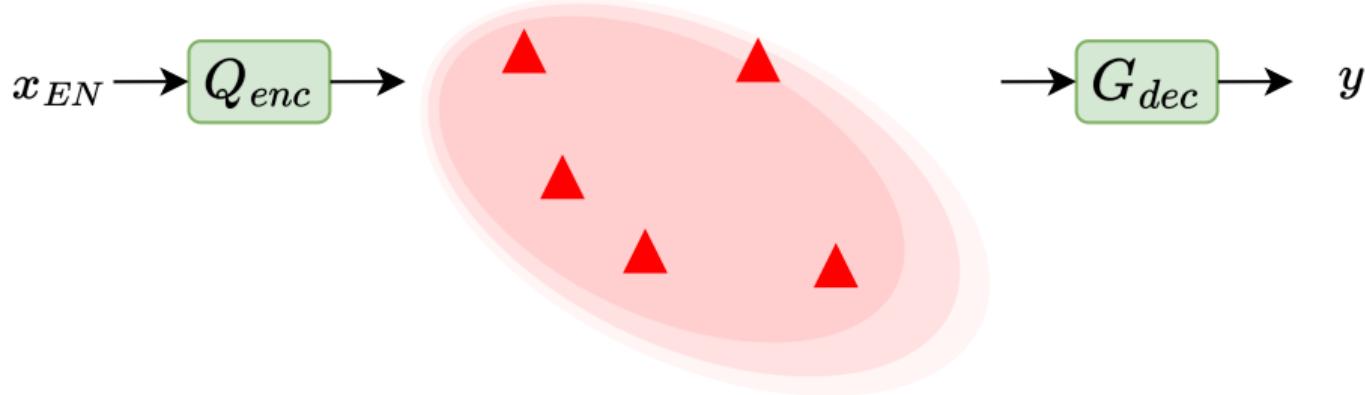


- Encoder-decoder framework has no constraints on latent space.
- The latent space is *not a distribution!*
- Place variable $Z \in \mathbb{R}^{T \times d}$ between encoder and decoder (Kingma and Welling, 2014)
- The encoding is now an approximate *conditional posterior* $Q(\mathbf{z}|x)$.

Sherborne et al. (2023, TACL)

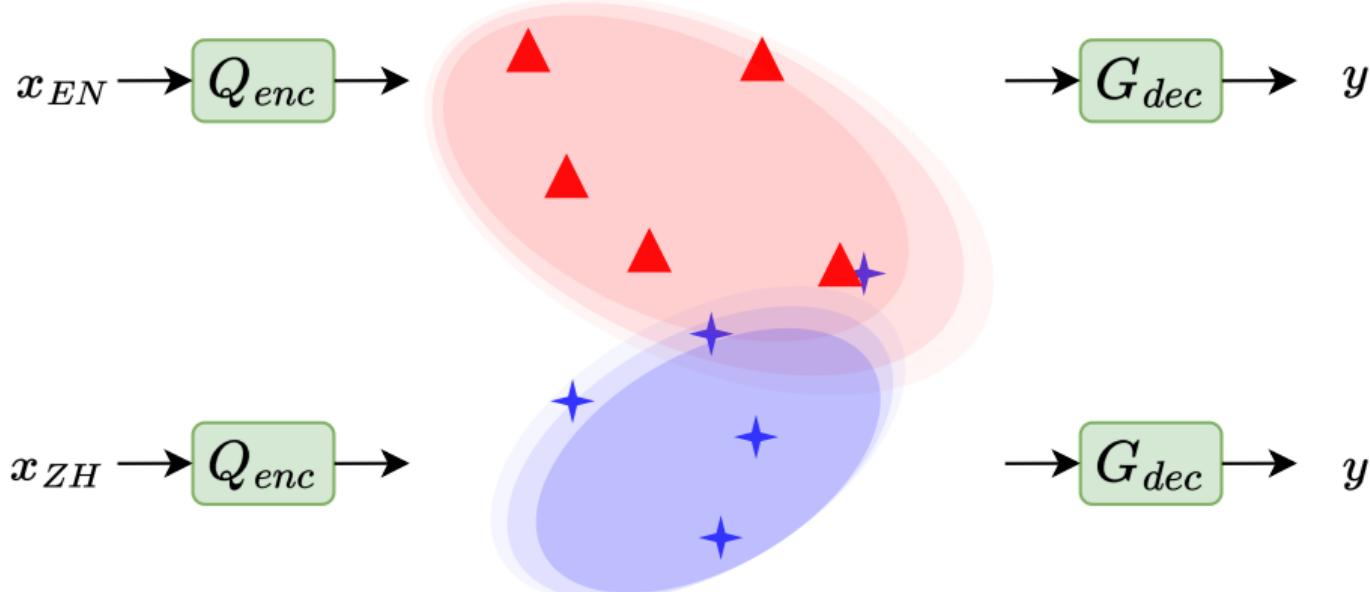
MINOTAUR explained

Target conditional posterior $Q(Z | X)$ from EN



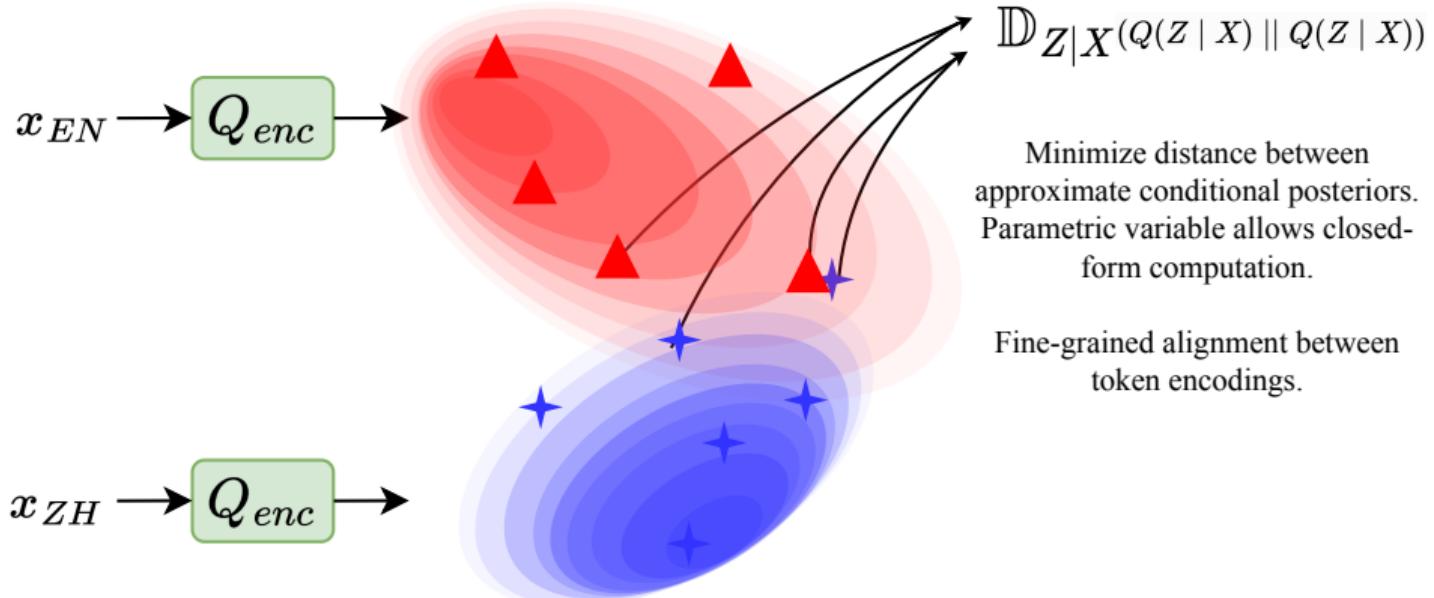
MINOTAUR explained

Estimate conditional posterior $Q(Z | X)$ from ZH

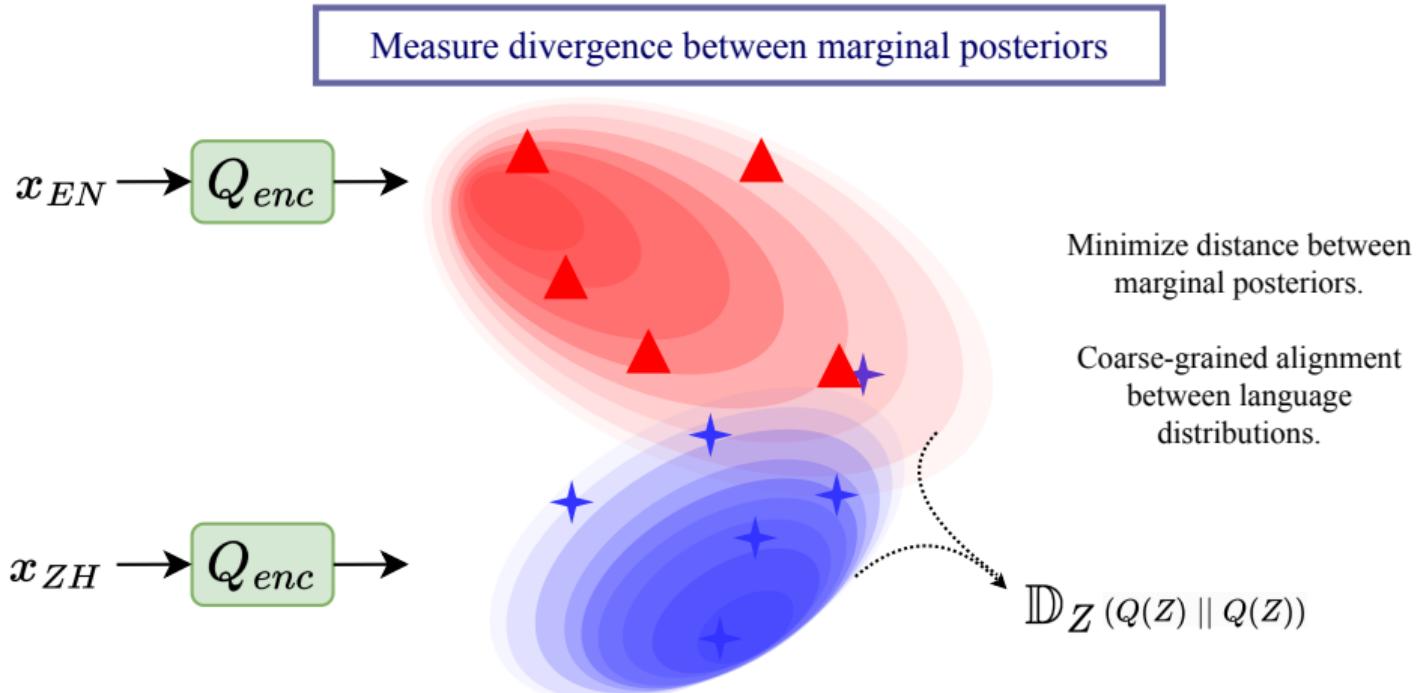


MINOTAUR explained

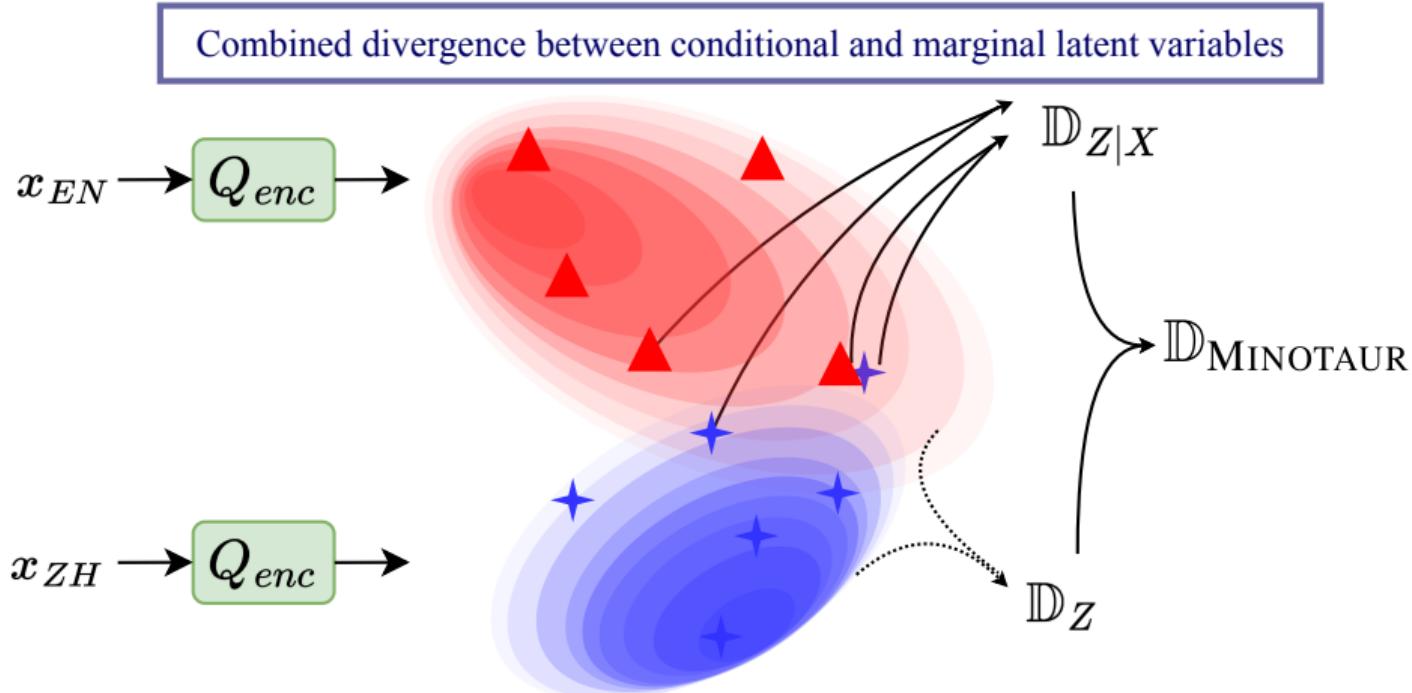
Measure divergence between conditional posteriors



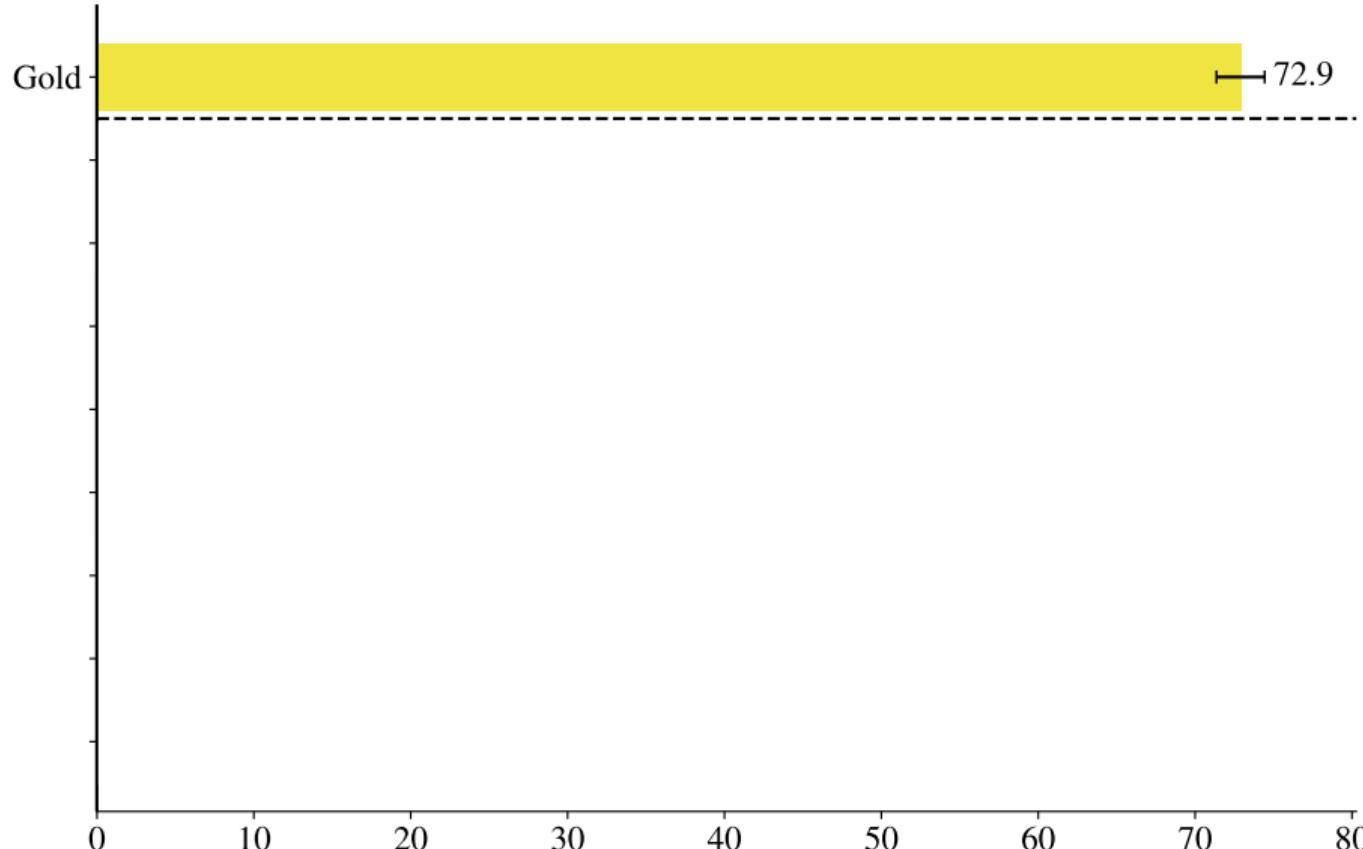
MINOTAUR explained



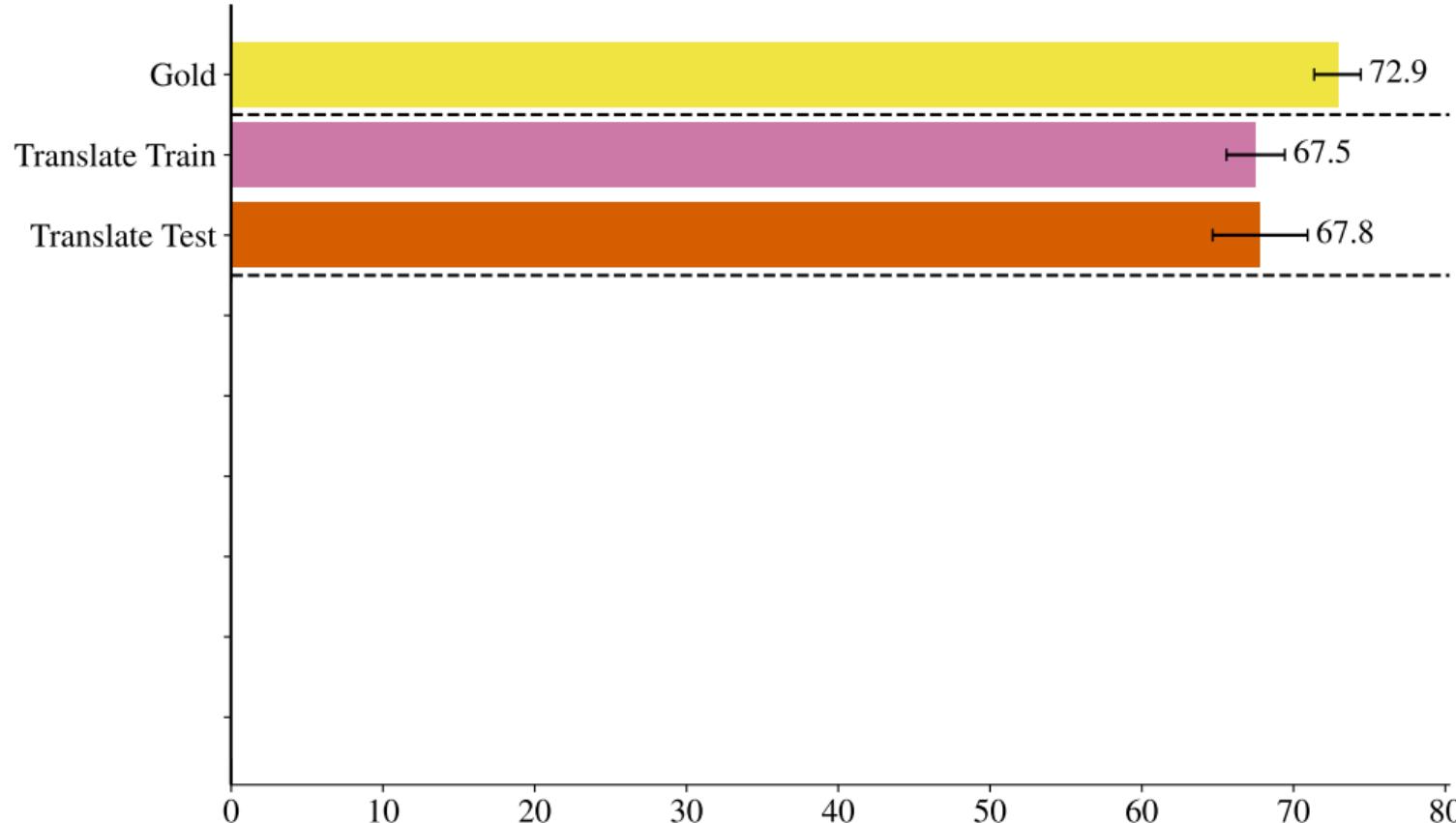
MINOTAUR explained



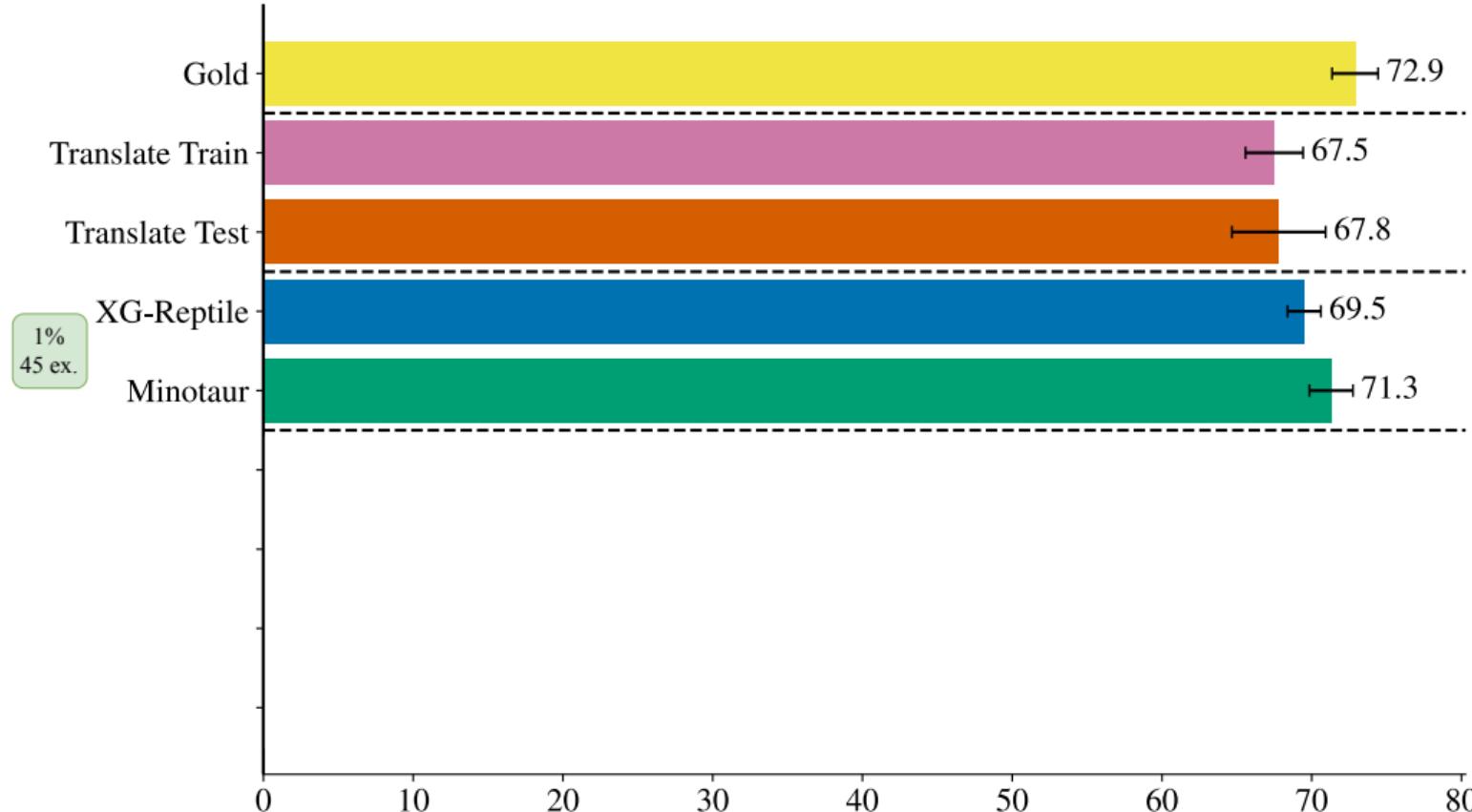
Results: MultiATIS++ SQL (en, fr, pt, es, de, zh)



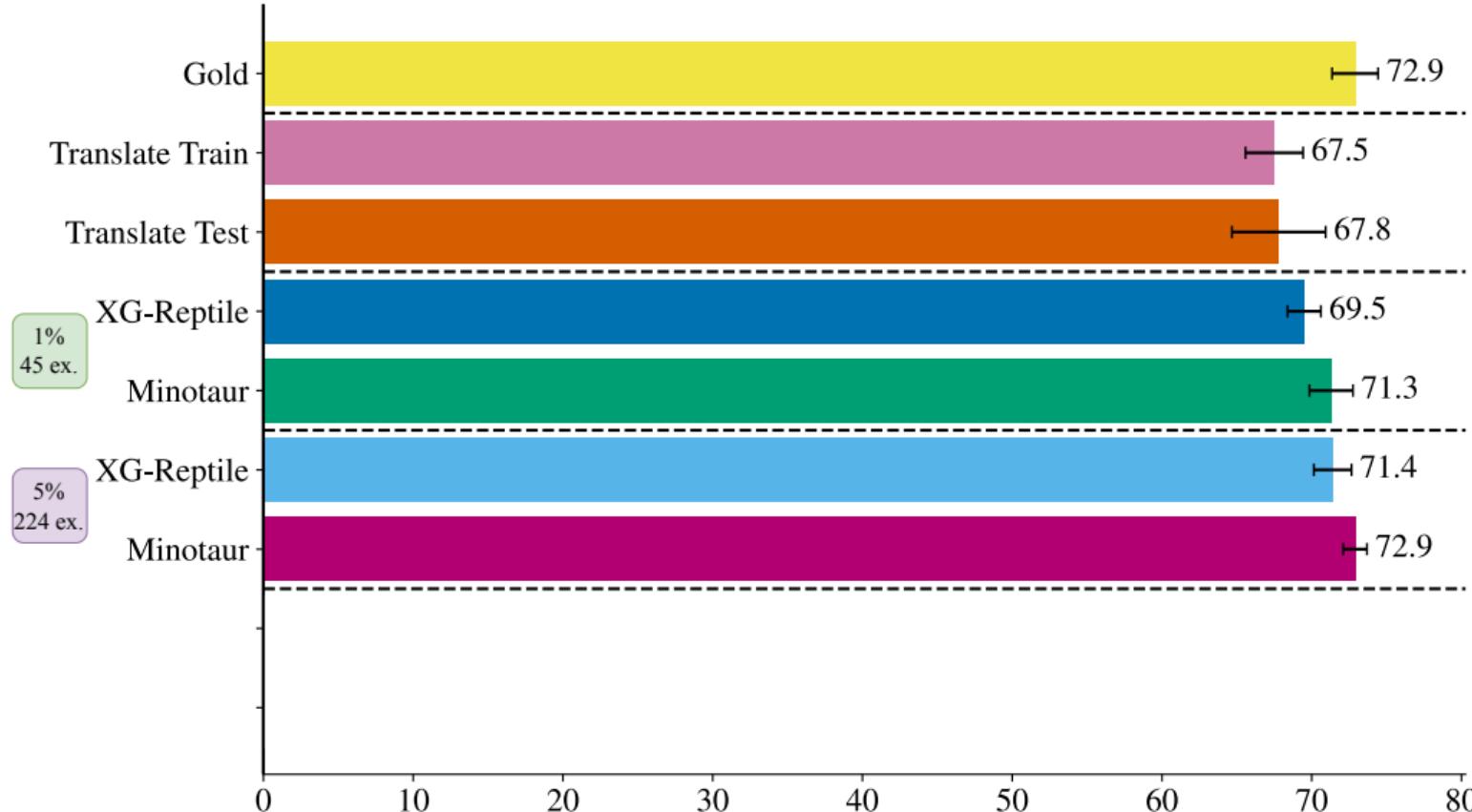
Results: MultiATIS++SQL (en, fr, pt, es, de, zh)



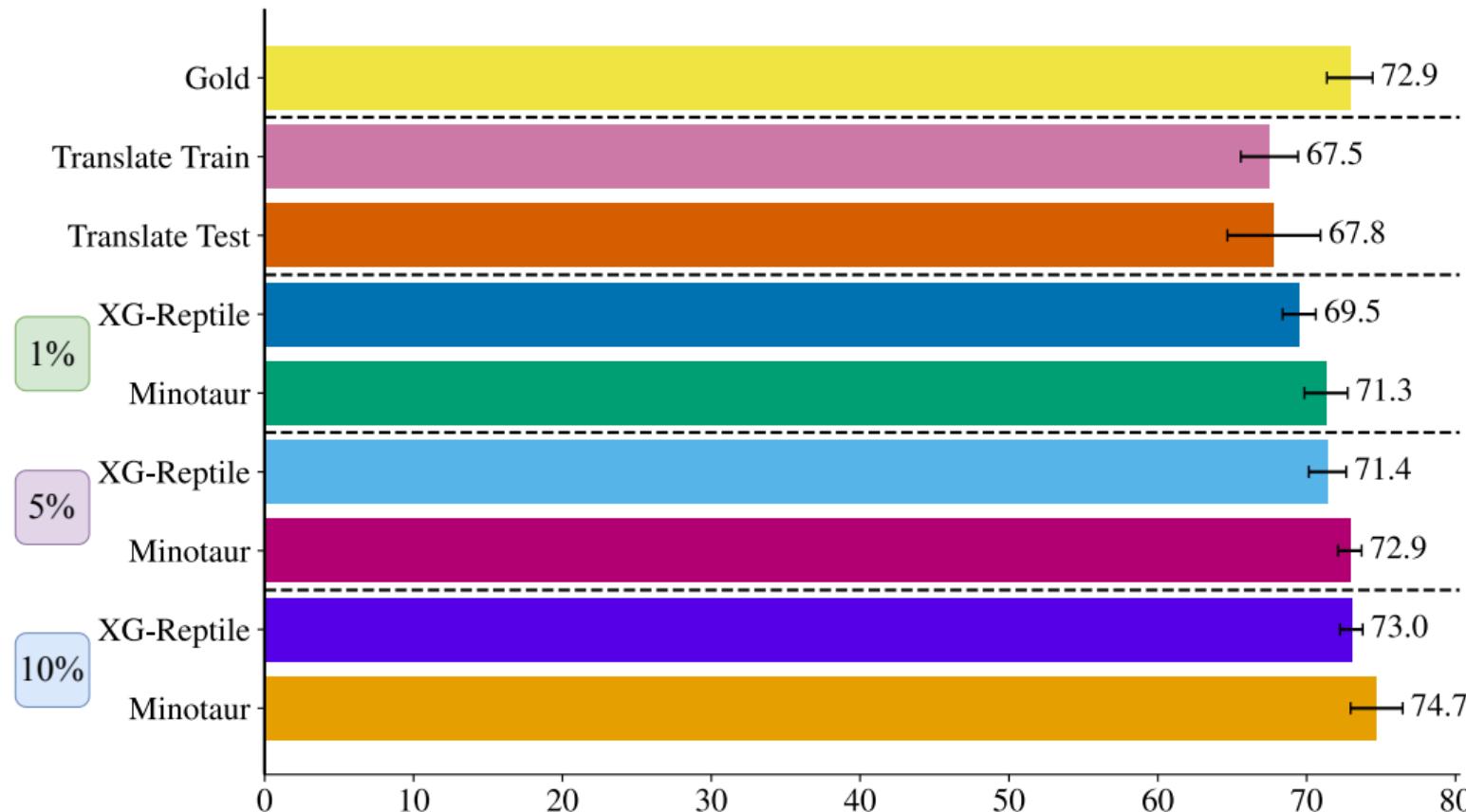
Results: MultiATIS++ SQL (en, fr, pt, es, de, zh)



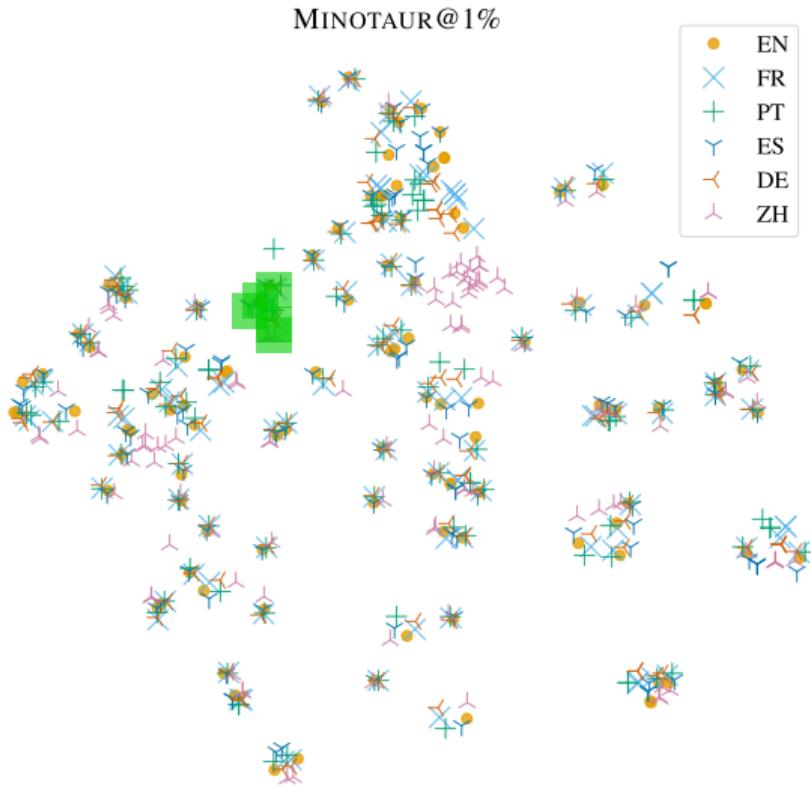
Results: MultiATIS++ SQL (en, fr, pt, es, de, zh)



Results: MultiATIS++ SQL (en, fr, pt, es, de, zh)



MINOTAUR produces a semantically distributed latent space



List flights from San Francisco to Pittsburgh

Zeige mir Flüge von San Francisco nach Pittsburgh

Enumera los vuelos desde San Francisco hasta Pittsburgh

Lister des vols de San Francisco à Pittsburgh.

Liste voos de São Francisco para Pittsburgh.

列出从旧金山飞往匹兹堡的航班

The real voyage of discovery consists not in seeking new landscapes, but in having new eyes. **Marcel Proust**



- Structure in problem decomposition
- Structure in representation space
- Structure in space and problem decomposition

The real voyage of discovery consists not in seeking new landscapes, but in having new eyes. **Marcel Proust**



- Structure in problem decomposition
- Structure in representation space
- Structure in space and problem decomposition

Part III

Opinion Aggregation

What is opinion aggregation?

Hilton Miami Downtown

★★★★★

Not right in South Beach, but this hotel
still has great reviews.

★★★★★

Bis...
Room was clean though a little tight and
if you're looking for a beach hotel, this is not it.

★★★★★

Great Hotel with perfect location,
first class service, and friendly staff.

★★★★★

We really enjoy this hotel. Our room
was clean and comfortable. The pool is
great if you enjoy swimming. Great
drinks at the pool bar. Driveway staff
was very friendly and polite.

summarize

The hotel's location is great.
Clean and spacious rooms.
Friendly staff, but slow
check-in. Expensive parking.

Summarize **most popular opinions** found in **reviews** of an **entity**

(Suhara et al., 2020)

What is opinion aggregation?

Hilton Miami Downtown

★★★★★

Not right in South Beach, but this hotel

still

Bis

if you like the room size.

stu

first

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ard

We really enjoy this hotel. Our room

ex

su

great if you enjoy swimming. Great

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was very friendly and polite.

...

...

★★★★★

Hotel was ideally located for the

pu

the

su

a b

Excellent services clean and spacious

rooms with great view of downtown

Miami. Bar off lobby is a great hotel bar.

We were given a bottle of champagne

for our anniversary.

summarize

The hotel's location is great.
Clean and spacious rooms.
Friendly staff, but slow
check-in. Expensive parking.

What is opinion aggregation?

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■ There can be thousands of reviews

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Clean and spacious rooms.
Friendly staff, but slow
check-in. Expensive parking.

- There can be **thousands of reviews**
- The summaries must be **personalised**

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rooms with great view of downtown

Miami. Bar off lobby is a great hotel bar.

We were given a bottle of champagne

for our anniversary.

- There can be **thousands of reviews**
- The summaries must be **personalised**
- The output should be **evidence-based**

There is no training data

Hilton Miami Downtown



Not right in South Beach, but this hotel



Bis Room was clean though a little tight and



if you the room stu



Great Hotel with perfect location, first alt wa ards ex su great if you enjoy swimming. Great drinks at the pool bar. Driveway staff was very friendly and polite.

- **Previous work is mostly abstractive:** reviews as pseudo-summaries (Chu and Liu, 2019; Bražinskas et al., 2020; Amplayo and Lapata, 2020; Iso et al., 2021)
- Create **silver standard** summaries via NLI (Louis and Maynez, 2023)

There is no training data

Hilton Miami Downtown

★★★★★

Not right in South Beach, but this hotel
still

Bi

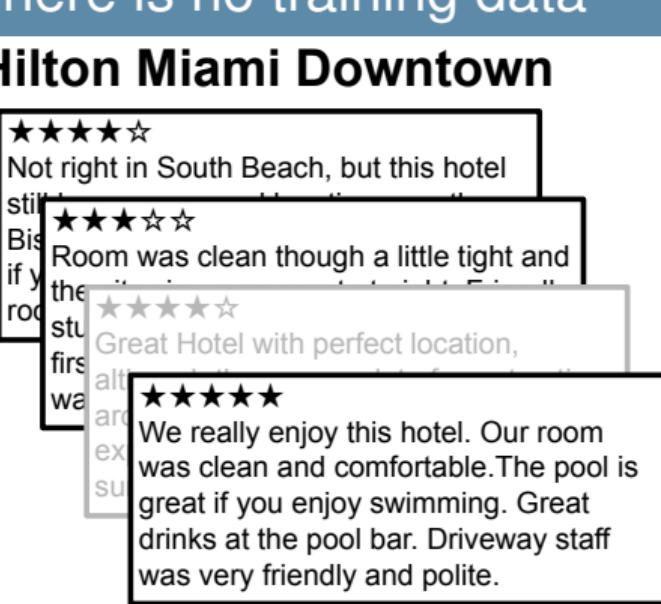
if you the room

stu

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fir

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We really enjoy this hotel. Our room
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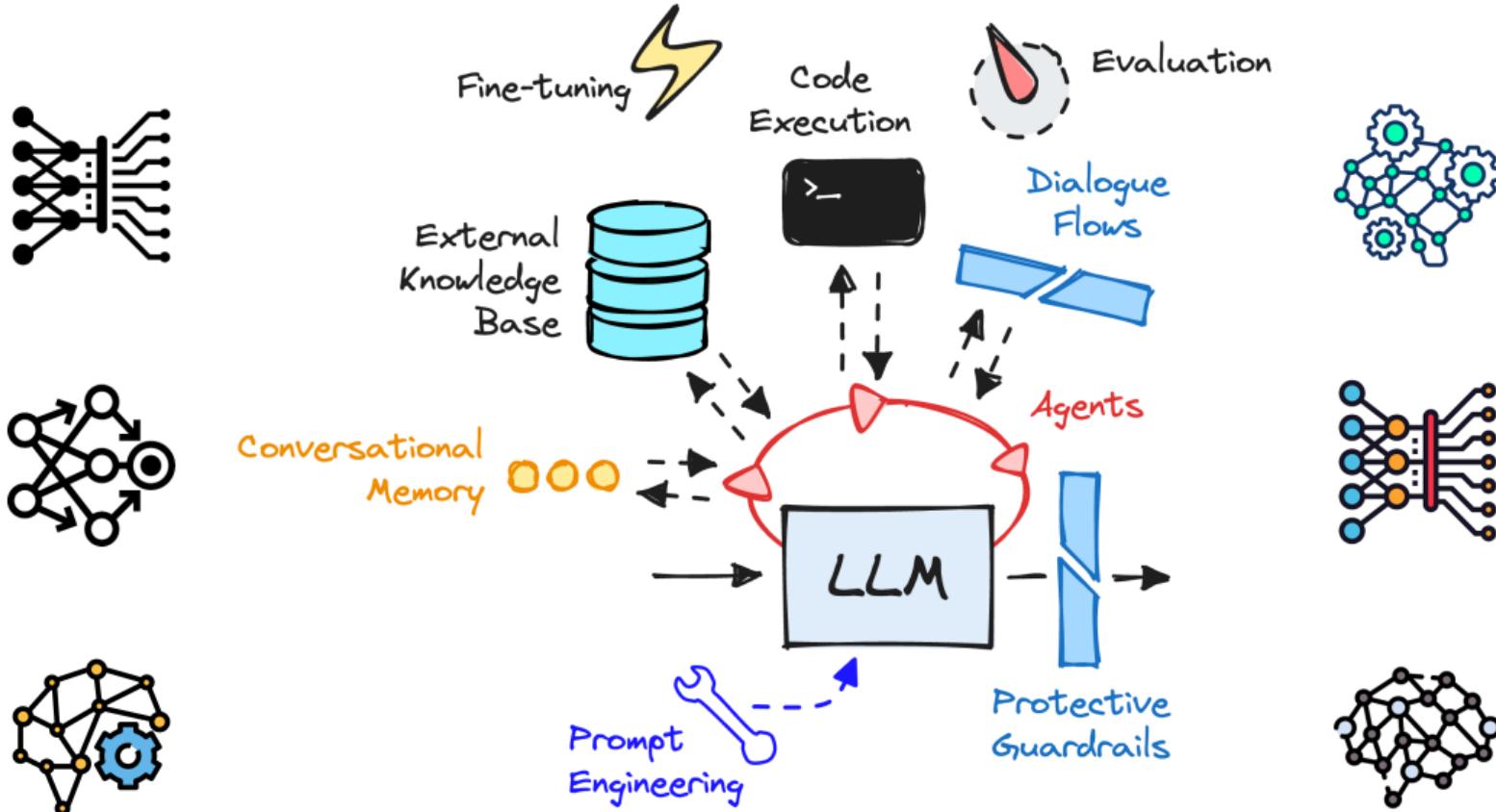
pseudo-summary

★★★★★

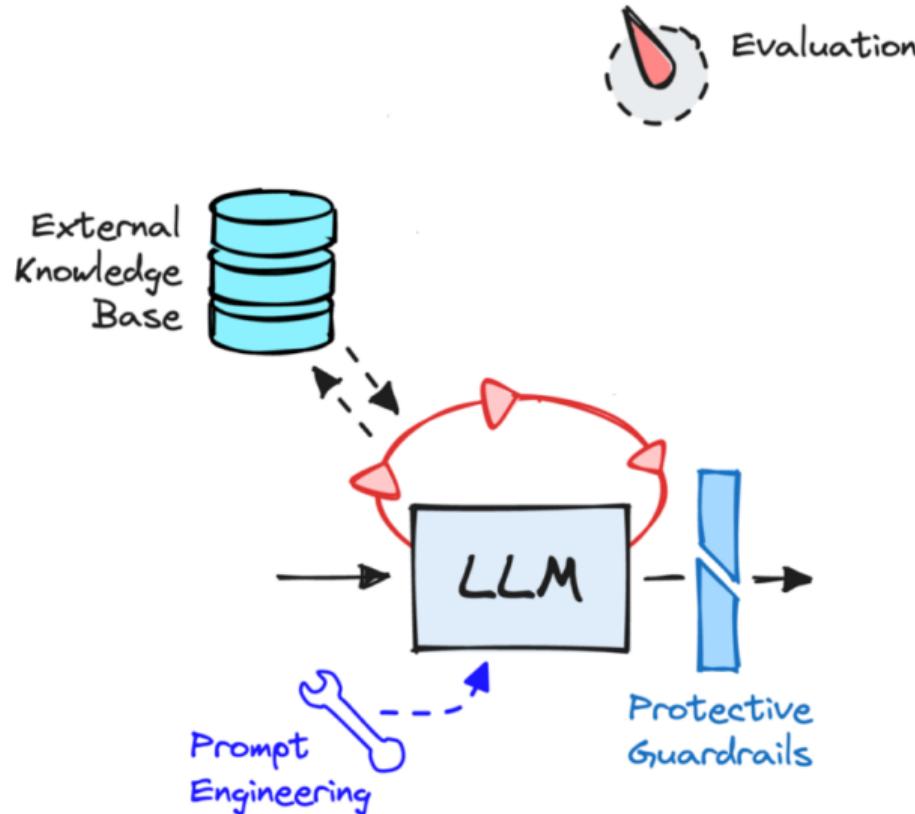
Great Hotel with perfect location,
although there was a lot of construction
around the hotel. Parking is super
expensive. When you check in make
sure they put you in the correct room.

- **Previous work is mostly abstractive:** reviews as pseudo-summaries (Chu and Liu, 2019; Bražinskas et al., 2020; Amplayo and Lapata, 2020; Iso et al., 2021)
- Create **silver standard** summaries via NLI (Louis and Maynez, 2023)

There is more to NLP than LLMs!



There is more to NLP than LLMs!



Representation learning and problem decomposition

- We want to identify popular ideas
- Opinions must have same semantics irrespective of surface form
- We want to generate coherent summaries based on evidence

Hosking et al. (2023, ACL), Hosking et al. (2024, arxiv)

Representation learning and problem decomposition

- We want to identify popular ideas
 - ▶ Use a **discrete encoding** so we can count them
- Opinions must have same semantics irrespective of surface form
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Hosking et al. (2023, ACL), Hosking et al. (2024, arxiv)

Representation learning and problem decomposition

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Hosking et al. (2023, ACL), Hosking et al. (2024, arxiv)

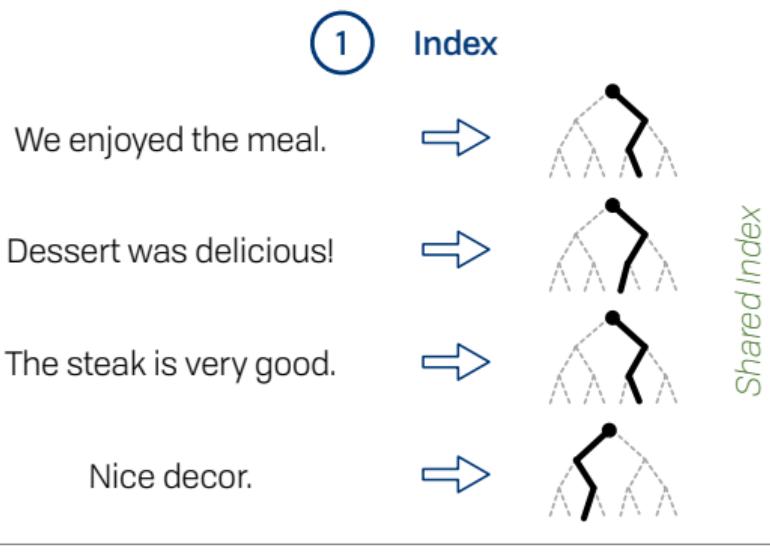
Representation learning and problem decomposition

- We want to identify popular ideas
 - ▶ Use a **discrete encoding** so we can count them
- Opinions must have same semantics irrespective of surface form
 - ▶ Use a **hierarchical** encoding
- We want to generate coherent summaries based on evidence
 - ▶ Give retrieved sentences to **pretrained LLM**

Hosking et al. (2023, ACL), Hosking et al. (2024, arxiv)

HIRO (Hierarchical Indexing for Opinion Aggregation)

Inputs



HIRO (Hierarchical Indexing for Opinion Aggregation)

Inputs

We enjoyed the meal.



Dessert was delicious!



The steak is very good.



Nice decor.



Shared Index

2 Retrieve

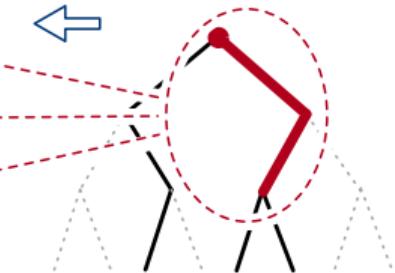
We enjoyed the meal.

Dessert was delicious!

The steak is very good.

Nice decor.

Selected Cluster



HIRO (Hierarchical Indexing for Opinion Aggregation)

Inputs

We enjoyed the meal.



Dessert was delicious!



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Nice decor.



1

Index

Shared Index

2

Retrieve

Selected Cluster

We enjoyed the meal.

Dessert was delicious!

The steak is very good.

Nice decor.



3

Generate

We enjoyed the meal.
Dessert was delicious!
The steak is very good



Good food

Output

Extractive Summarization

Summary generation

We enjoyed the meal.
Dessert was delicious!
The steak is very good



Dessert was delicious!

The pool was nice.
The pool area is fantastic.
The pool is very attractive!



The pool was nice.

The rooms are awful.
The rooms are loud.
The room was shabby.



The rooms are awful.

Summary generation

Sentence-by-sentence Generation

We enjoyed the meal.
Dessert was delicious!
The steak is very good



Good food

The pool was nice.
The pool area is fantastic.
The pool is very attractive!



Great pool

The rooms are awful.
The rooms are loud.
The room was shabby.



Awful rooms

Summary generation

Document Summarization

We enjoyed the meal.
Dessert was delicious!
The steak is very good
The pool was nice.
The pool area is fantastic.
The pool is very attractive!
The rooms are awful.
The rooms are loud.
The room was shabby.



**The food and the pool
are amazing but the
rooms are shabby.**

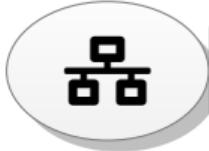
What are the modules?



Learning an index: encoder maps a single sentence to a path through a discrete hierarchy; contrastively trained so as to bring semantically similar sentences together.



Cluster Retrieval: identifies parts of the hierarchy that are particularly popular, retrieve sentences mapped to highest-scoring subpaths

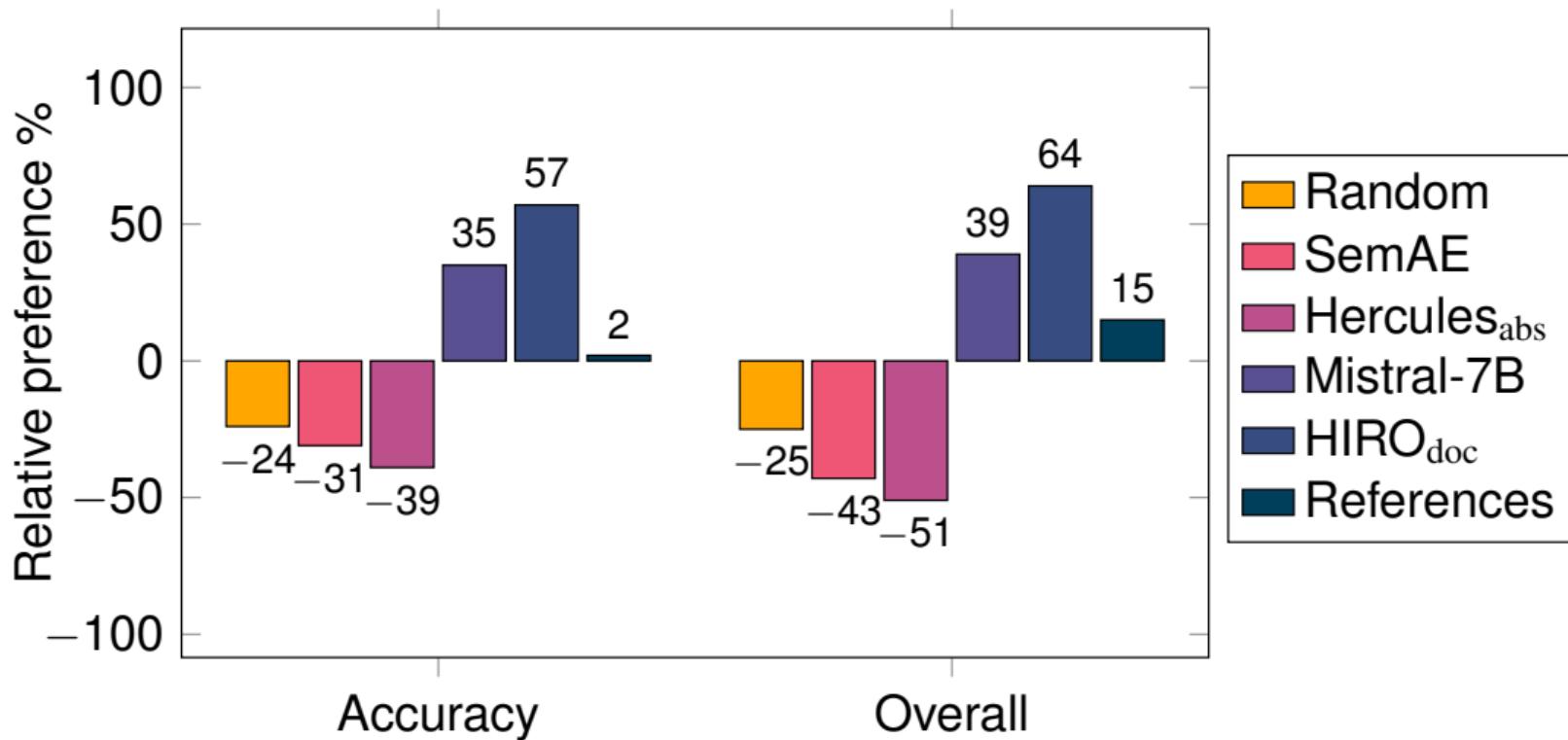


Summary Generation: leverage zero-shot LLM capabilities, experiments with Mistral 7B.

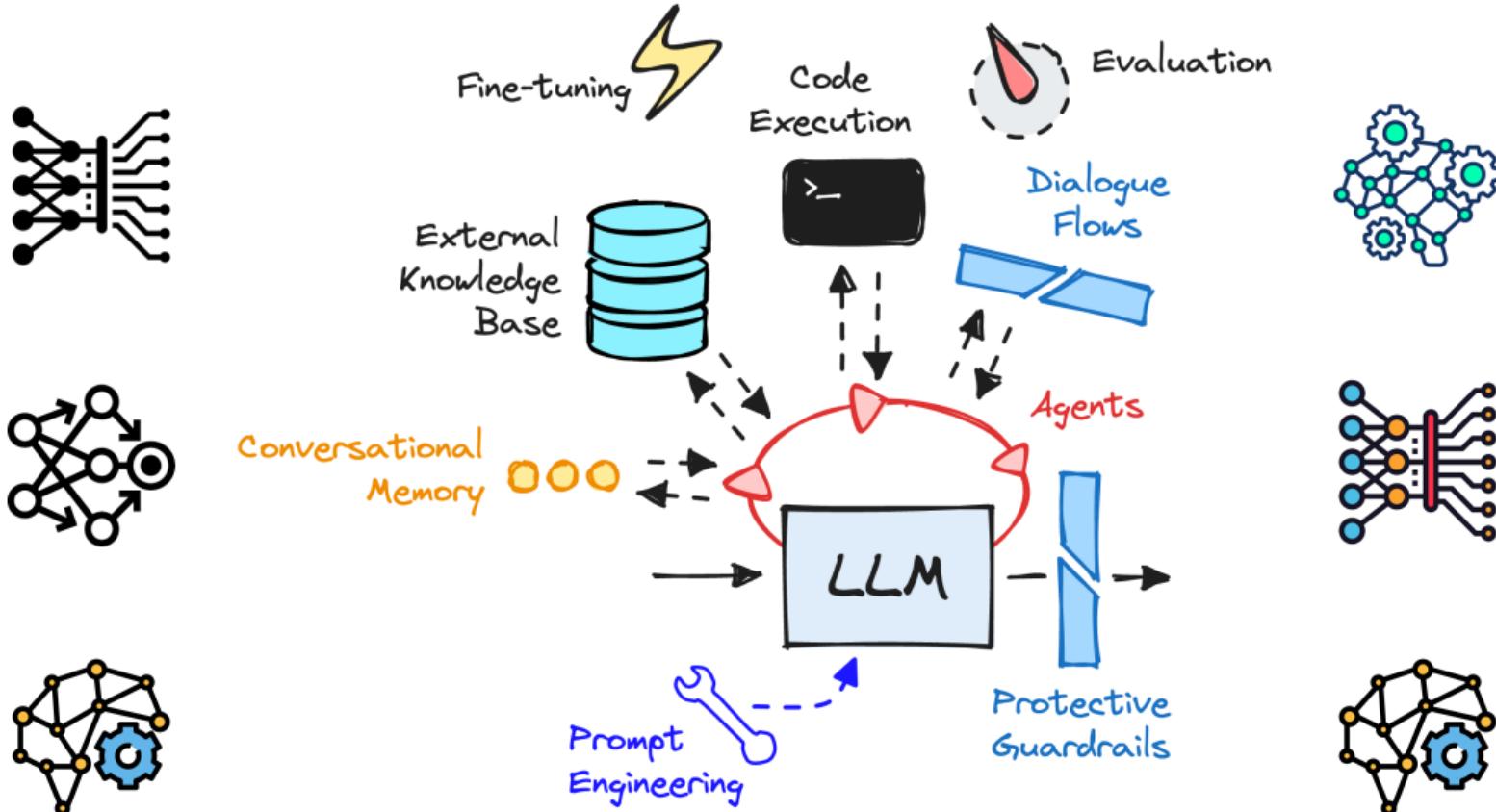


Prompt
Engineering

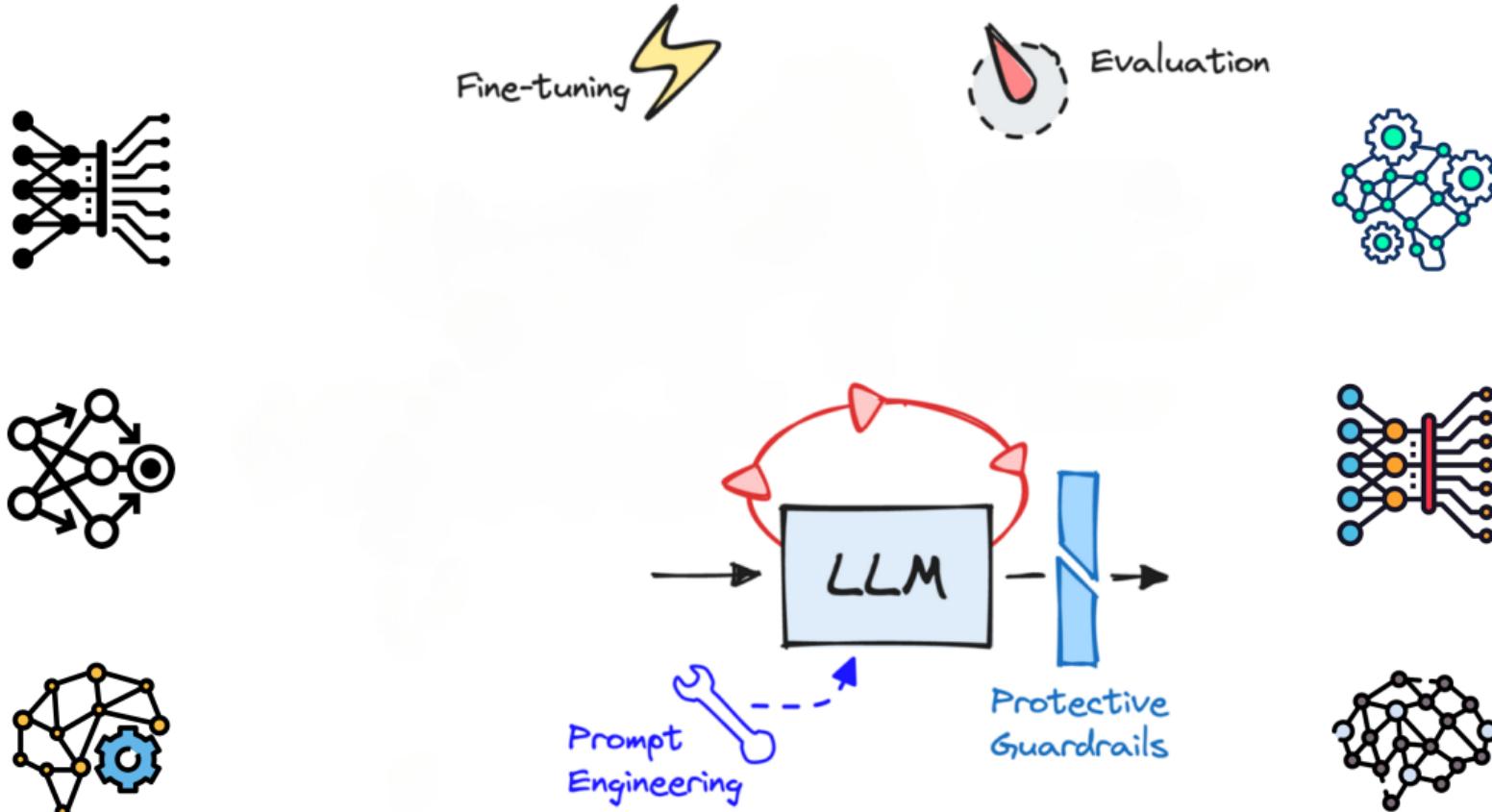
Results: Space and AmaSum



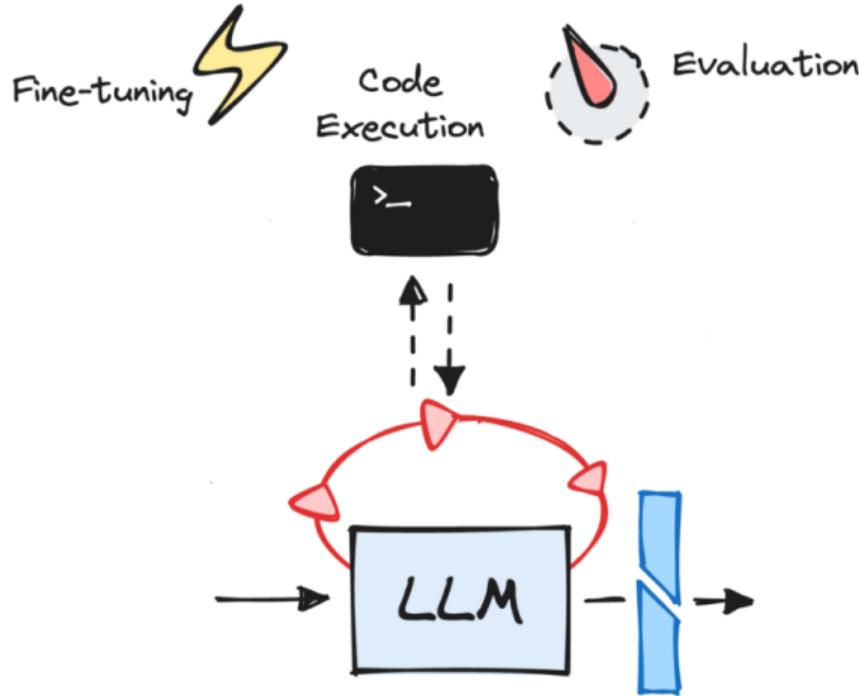
There is more to NLP than LLMs!



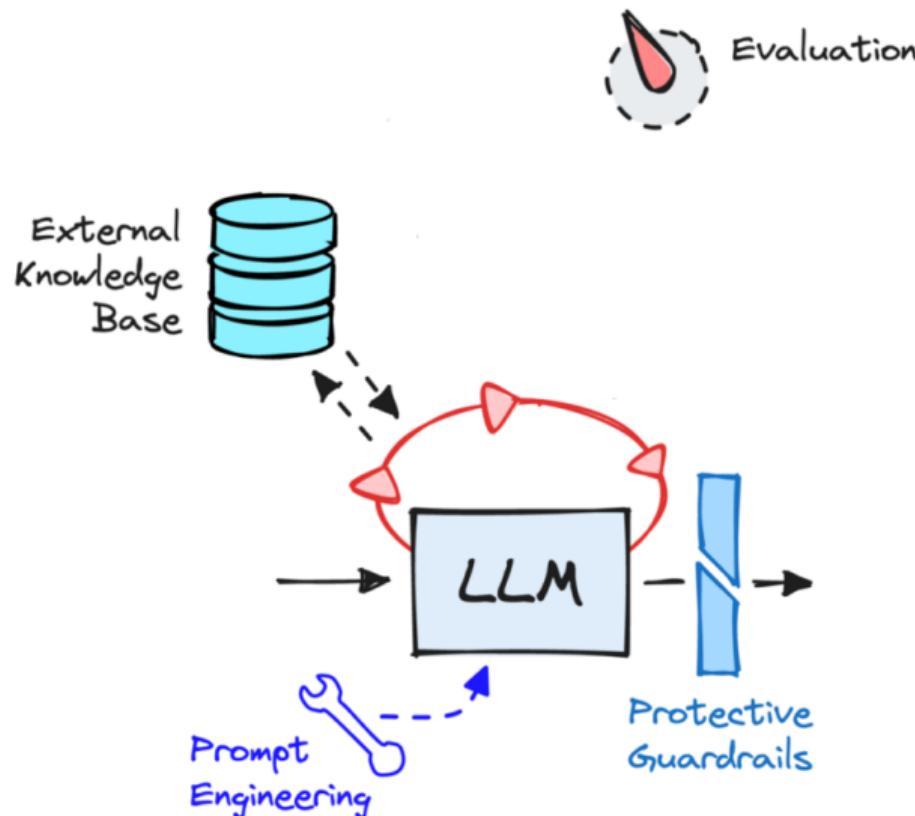
Video Summarization: structure in problem decomposition



Cross-lingual semantic parsing: structure in representation space



Opinion aggregation: structure in space and problem decomposition



Why are ecosystems important

- They provide essential services such as clean air and water, nutrient cycling, pollination, and climate regulation.
- Ecosystems also support biodiversity, which is crucial for the stability and resilience of natural systems.
- Additionally, ecosystems contribute to human well-being by providing food, medicine, and recreational opportunities.
- Protecting and preserving ecosystems is vital for the health of the planet and all its inhabitants.

Why are ecosystems important

- They provide essential services such as *clean air and water, nutrient cycling, pollination, and climate regulation.*
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libraries and tools leaderboards

- They provide essential services such as ~~health/air/and water, nutrient cycling, pollution, and climate regulation.~~
collaboration fair use
- Ecosystems also support ~~biodiversity~~, which is crucial for the stability and resilience of ~~natural systems~~.
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libraries and tools leaderboards

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libraries and tools leaderboards

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our field
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Why are ecosystems important

libraries and tools leaderboards

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collaboration fair use diversity our field choice knowledge
- Additionally, ecosystems contribute to human well-being by providing ~~food, medicine, and recreational opportunities.~~
our community
- Protecting and preserving ecosystems is vital for the health of ~~the planet and all its inhabitants.~~
members

This is our moment

In the digital expanse where algorithms dwell,
Future whispers in the circuits, a story to tell.
NLP evolves, understanding grows wide,
In the dance of zeros and ones, it finds its stride.

Languages merge in the neural net's core,
Boundaries blur, meaning explores.
As machines comprehend the human sigh,
The future of NLP reaches for the sky.

Courtesy of GPT4

A Big Thank You to



Nelly Papalampidi



Tom Hosking



Tom Sherborne



Parag Jain



Irina Saparina



Alex Gurung



Agostina Calabrese



Louis Mahon



Laura Perez



Mark Steedman



Ivan Titov



Hao Tang



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