

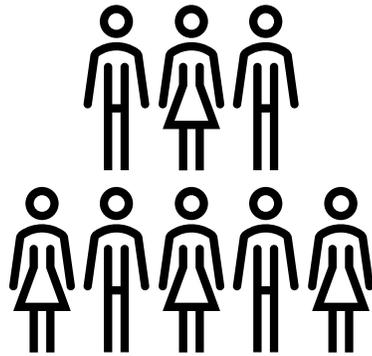
# Generating Data Augmentation Queries Using Large Language Models

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# Drug Repositioning Can Save Lives



Patients with Castleman's disease

- Rare disease
- Potentially fatal: causes severe inflammation
- No effective treatments currently exist



*Unfortunate reality:*



**Too rare:** no financial incentive for companies to develop treatments

*Alternative:*



Find an existing drug to treat Castleman's disease

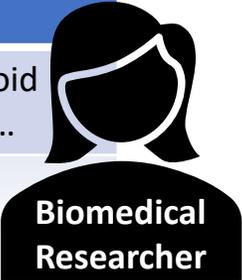


# Identify a Candidate Drug

## Find a candidate drug

### FDA-Approved Drugs

brand_name	class	uses
Humira	TNF inhibitor	rheumatoid arthritis ...
Enbrel	TNF inhibitor	plaque psoriasis



Biomedical Researcher

Local Data Source

Castleman's causes severe inflammation...

**Humira** is used to treat conditions involving severe inflammation

**Candidate drug:** Humira

**Next step:** gather more information about Humira:

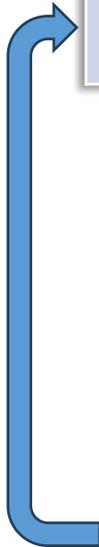
- Will it help or hurt?



# Find External Sources

Local entity:

brand_name	class	uses
Humira	TNF inhibitor	rheumatoid arthritis ...



## FDA-Approved Drugs

brand name	class	uses
Humira	TNF inhibitor	rheumatoid arthritis ...
Enbrel	TNF inhibitor	plaque psoriasis

Local Data Source



## Generic Drugs

generic_name	adverse_effects
Adalimumab	After treatment with adalimumab ...
Etanercept	Etanercept binds specifically to tumor ...

External Data Source



## Bio Compounds

formula	mechanisms
$C_{6428}H_{9912}N_{1694}O_{1987}S_{46}$	Binds with specificity to tumor ...
$C_{2224}H_{3475}N_{621}O_{698}S_{36}$	There are two distinct receptors ...

External Data Source



# What we Want: Info Relevant to Humira

Local entity:

brand_name	class	uses
Humira	TNF inhibitor	rheumatoid arthritis ...

*FDA-Approved Drugs*

brand name	class	uses
Humira	TNF inhibitor	rheumatoid arthritis ...
Enbrel	TNF inhibitor	plaque psoriasis

Local Data Source



Relevant external entities

*Generic Drugs*

generic name	adverse effects
Adalimumab	After treatment with adalimumab ...
Etanercept	Etanercept binds specifically to tumor ...

External Data Source

*Bio Compounds*

formula	mechanisms
$C_{6428}H_{9912}N_{1694}O_{1987}S_{46}$	Binds with specificity to tumor ...
$C_{2224}H_{3475}N_{621}O_{698}S_{36}$	There are two distinct receptors ...

External Data Source



# Augment Humira With that Relevant Info

brand_name	class	uses	adverse_effects
Humira	TNF inhibitor	rheumatoid arthritis ...	After treatment with adalimumab ...

## mechanisms

Binds with specificity to tumor ...

## FDA-Approved Drugs

brand_name	class	uses
Humira	TNF inhibitor	rheumatoid arthritis ...
Enbrel	TNF inhibitor	plaque psoriasis

Local Data Source



## Generic Drugs

generic name	adverse effects
Adalimumab	After treatment with adalimumab ...
Etanercept	Etanercept binds specifically to tumor ...

External Data Source

## Bio Compounds

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External Data Source



# Manually Querying for Relevant External Entities

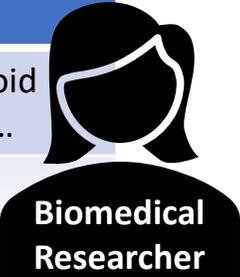
## Challenges:

- Many external data sources
- Data heterogeneity: different representations
  - **Humira** = **Adalimumab**  
 $= C_{6428}H_{9912}N_{1694}O_{1987}S_{46} = ???$

### FDA-Approved Drugs

brand_name	class	uses
Humira	TNF inhibitor	rheumatoid arthritis ...
Enbrel	TNF inhibitor	plaque psoriasis

**Local Data Source**



### Generic Drugs

generic_name	adverse_effects
Adalimumab	After treatment with

Et

### External Data Source

### Bio Compounds

formula	mechanisms
$C_{6428}H_{9912}N_{1694}O_{1987}S_{46}$	Binds with specificity

$C_{2}$

### External Data Source



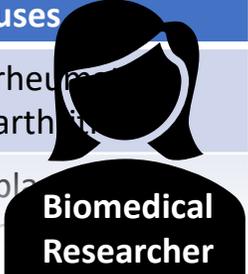
# 1<sup>st</sup> Try: Query = Too Specific to Local Source



Query = no relevant entities!

FDA-Approved Drugs		
brand_name	class	uses
Humira	TNF inhibitor	rheumatoid arthritis
Enbrel	TNF inhibitor	psoriasis

**Local Data Source**



**Generic Drugs**

generic_name	adverse_effects
Adalimumab	After treatment with

Humira  Search

**0 results**

External Data Source

**Bio Compounds**

formula	mechanisms
$C_{6428}H_{9912}N_{1694}O_{1987}S_{46}$	Binds with specificity

Humira  Search

**0 results**

External Data Source



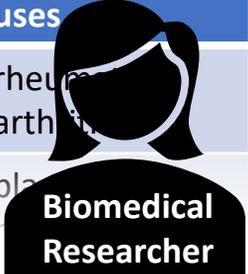
# 2<sup>nd</sup> Try: Query = Too General



Query = too many non-relevant entities

FDA-Approved Drugs		
brand_name	class	uses
Humira	TNF inhibitor	rheumatoid arthritis
Enbrel	TNF inhibitor	psoriasis

**Local Data Source**



**Generic Drugs**

generic_name	adverse_effects
Adalimumab	After treatment with

TNF plaque

**1090 results**

External Data Source

**Bio Compounds**

formula	mechanisms
$C_{6428}H_{9912}N_{1694}O_{1987}S_{46}$	Binds with specificity

rheumatoid arthritis

**243 results**

External Data Source



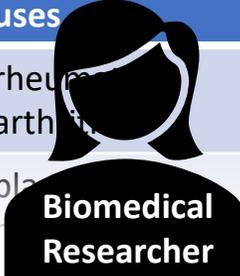
# N<sup>th</sup> Try: Just Right!



1. Retrieves relevant entity
2. ...and few non-relevant entities

FDA-Approved Drugs		
brand_name	class	uses
Humira	TNF inhibitor	rheumatoid arthritis
Enbrel	TNF inhibitor	psoriasis

**Local Data Source**



**Biomedical Researcher**

Adalimumab

Generic Drugs	
generic_name	adverse_effects
Adalimumab	After treatment with

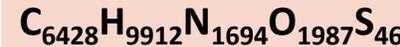
**9 results**

**External Data Source**

Bio Compounds	
formula	mechanisms
$C_{6428}H_{9912}N_{1694}O_{1987}S_{46}$	Binds with specificity

**14 results**

**External Data Source**



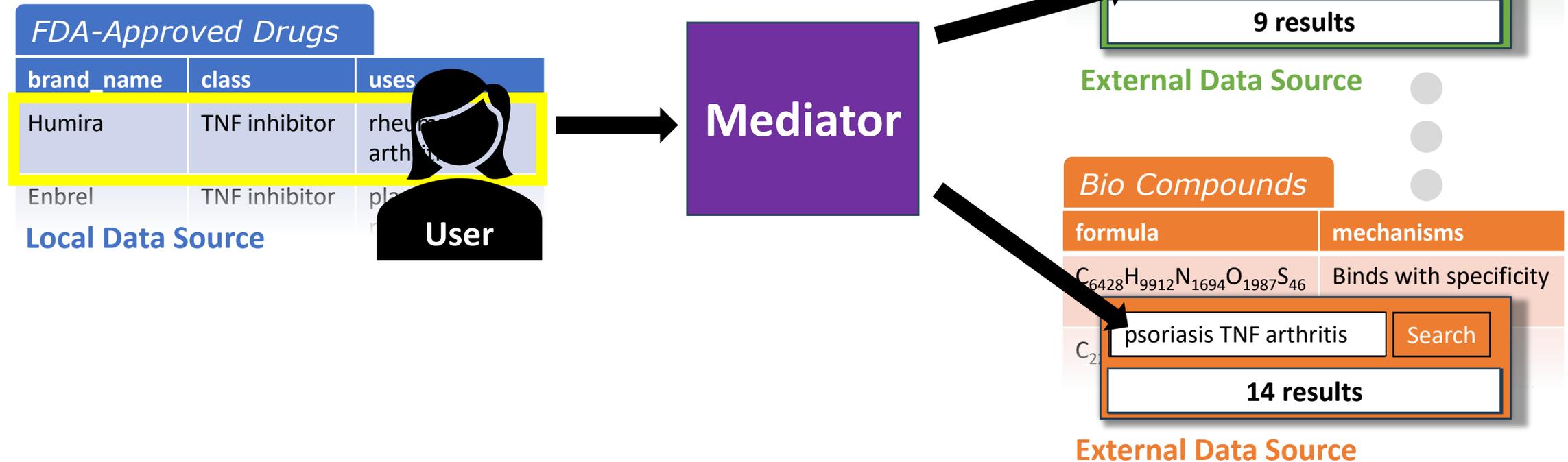
A lot of work!



# Alternative: Use a Mediator

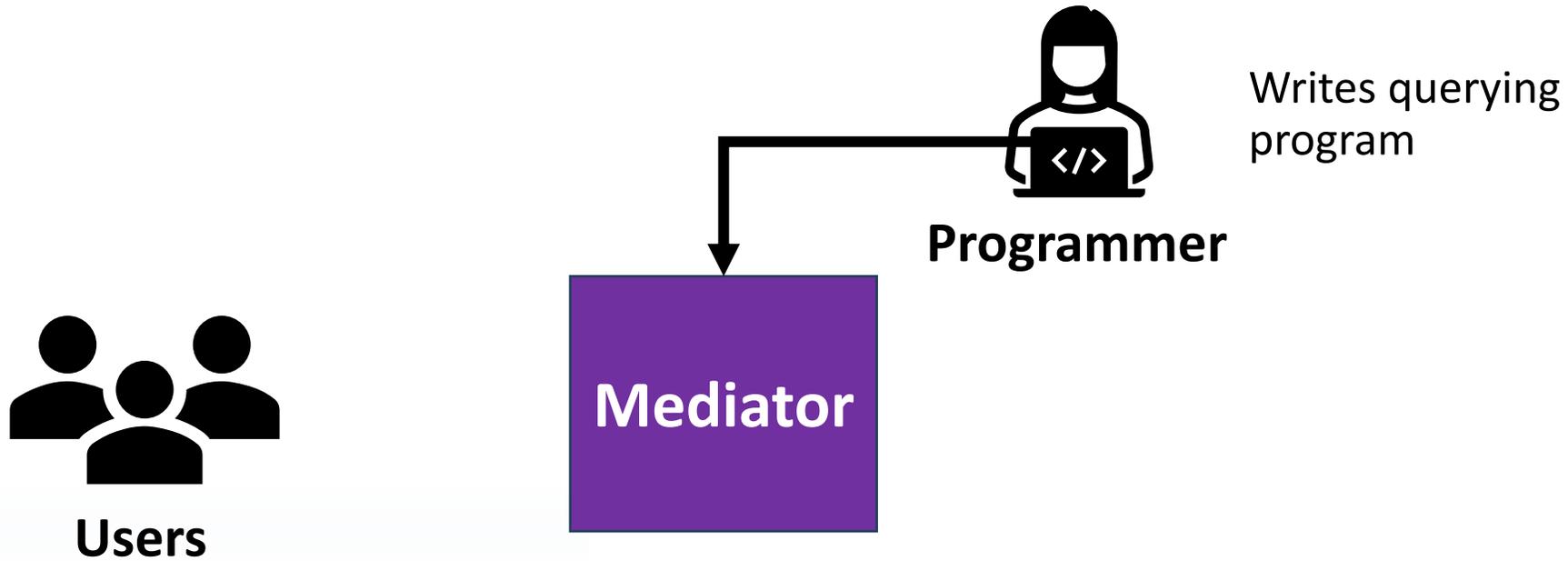
Query on behalf of the user:

1. User specifies *local* entity for augmentation
2. Mediator retrieves relevant information from external sources



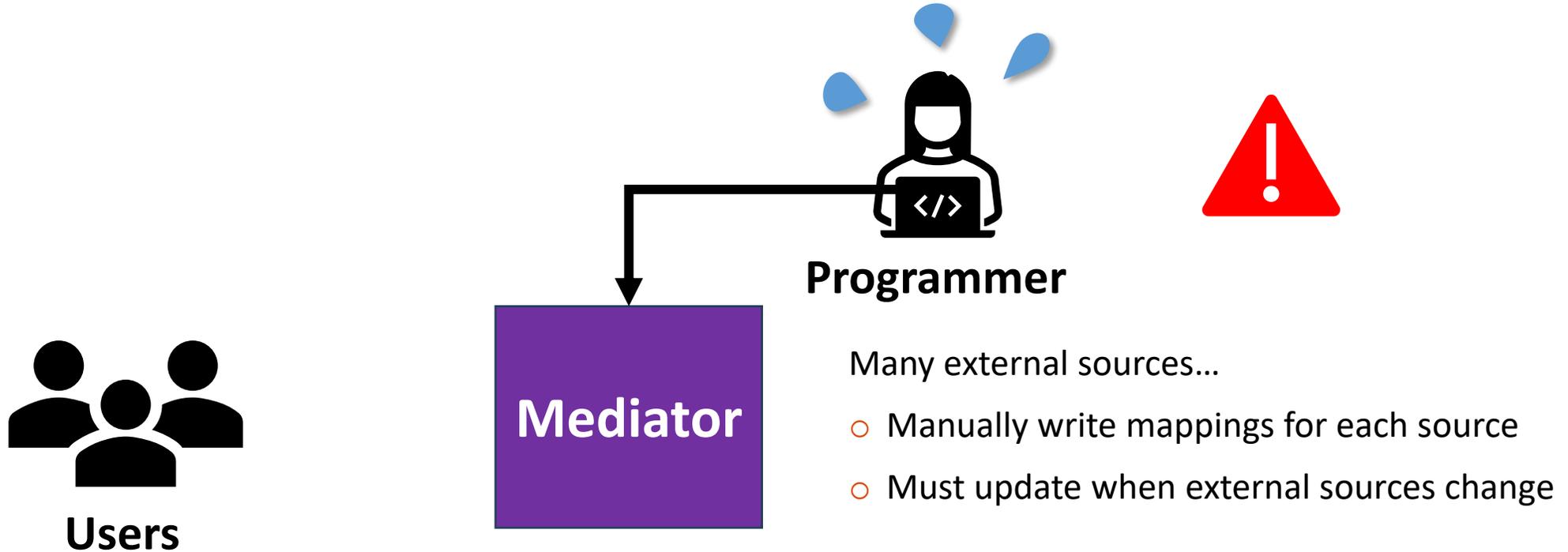


# Existing Work: Mediator Written By Hand



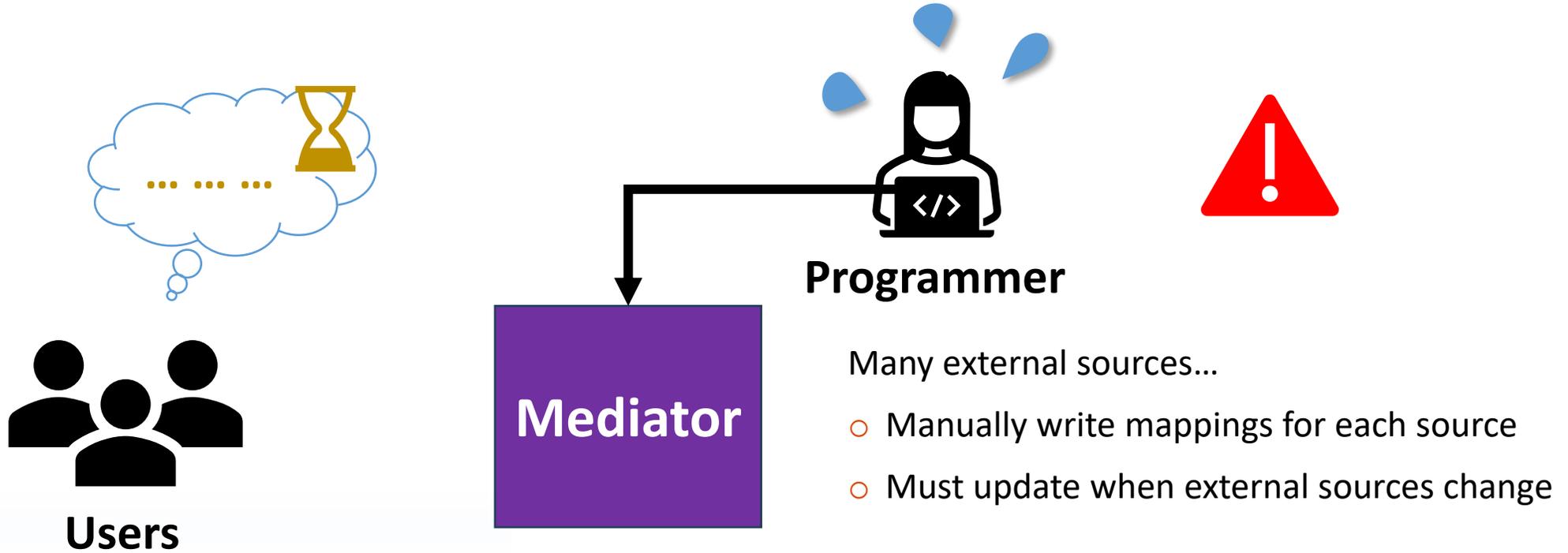


# Existing Work: Lots of Work!



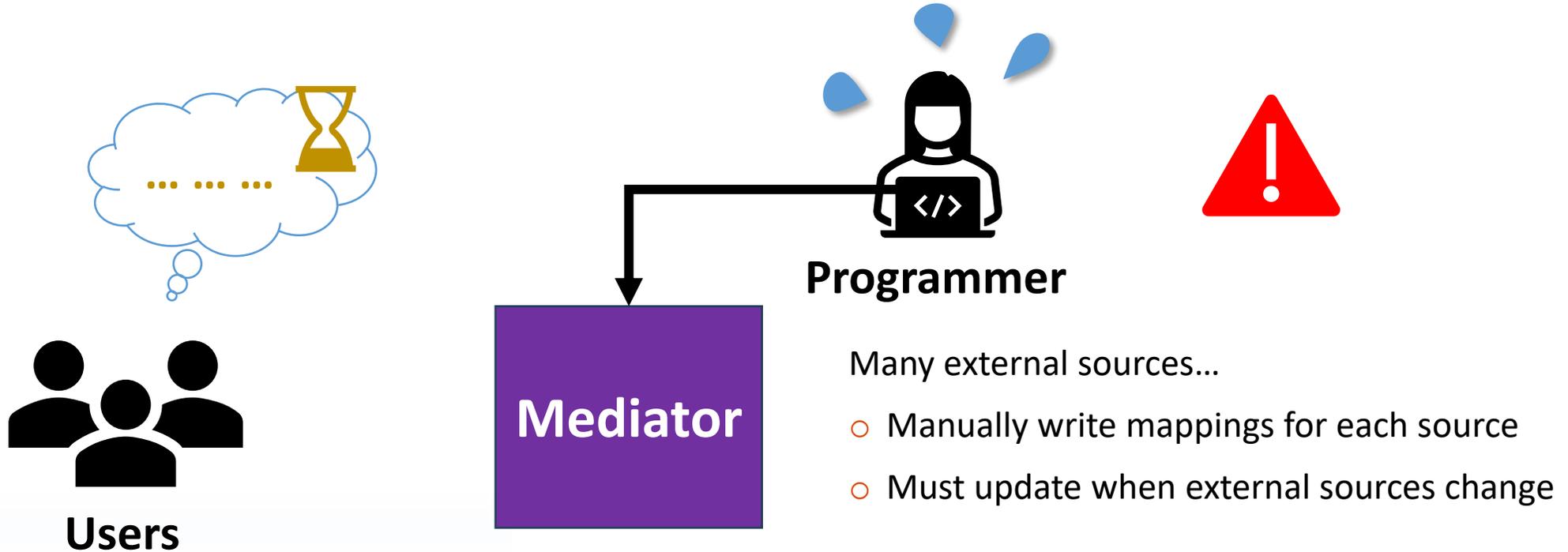


# Existing Work: Information Delays





# Existing Work: Resource Intensive!

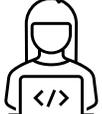


**For example:** the NIH funds a consortium of such systems (~14 systems)

- Just one system has 73 external datasources and millions of entities
- Costs NIH **US\$923 million per year!**



# Our Approach: Learn a Mediator

Reduce work  and delays  of writing the mediator *by hand*

Learn Mediator that maps **local entity** → “**Just right**” query

## FDA-Approved Drugs

brand name	class	uses
Humira	TNF inhibitor	rheumatoid arthritis ...
Enbrel	TNF inhibitor	plaque psoriasis ...

Local Data Source

Mediator

“Humira”

“TNF inhibitor  
crohns”

“TNF plaque”

Queries

keyword queries  
formed using  
words from  
**local entity's**  
content



# How Do We Learn the Mediator?

## Offline Learning:

1. Gather training data
2. Train mediator
3. Users query mediator



- Lots of expensive work
  - Hire domain experts to label data
  - External source updates → must repeat!
- Still delays...

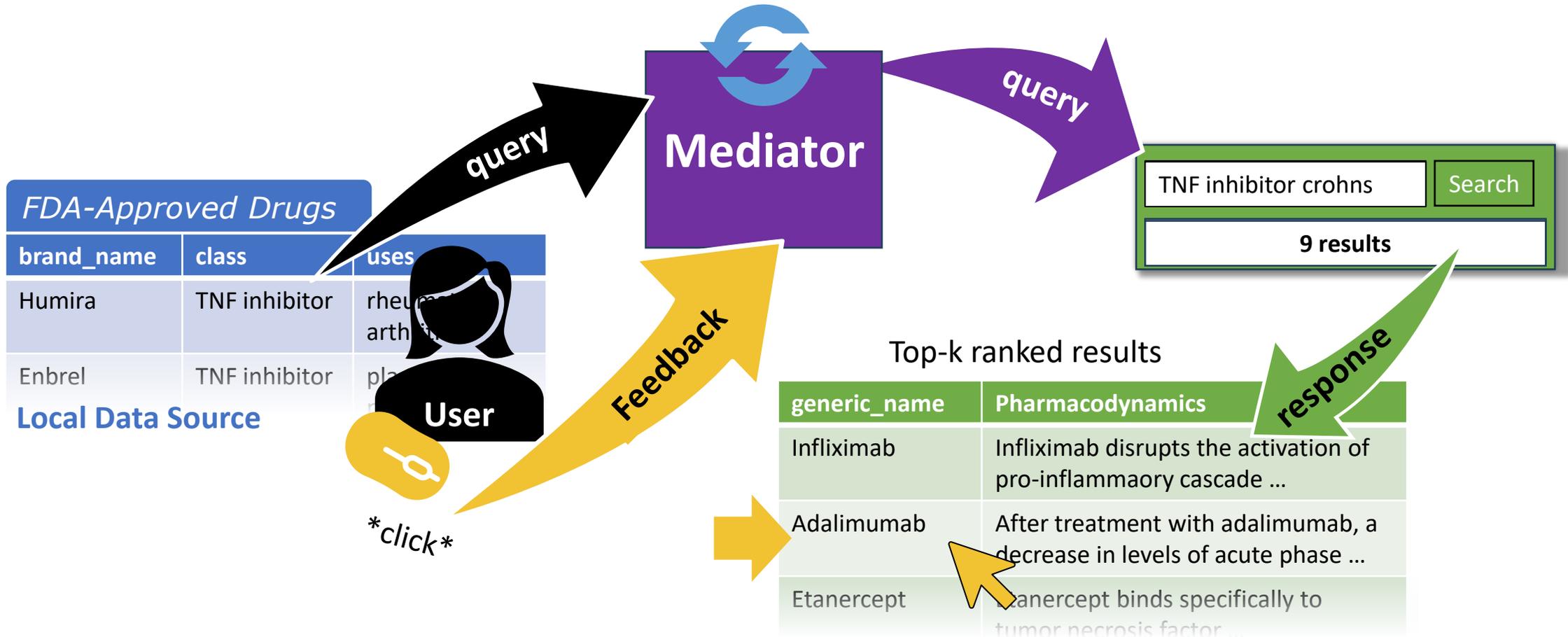
## Online Learning:

- Train mediator *while* users query it



# Online Learning Framework

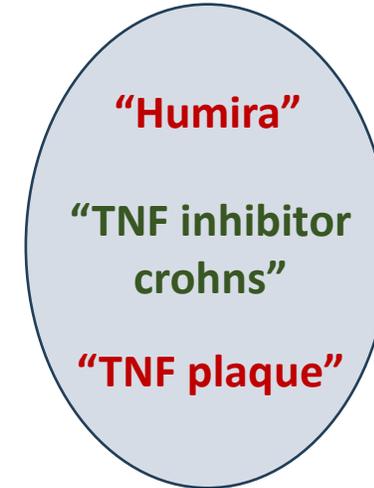
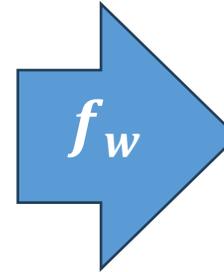
Refine understanding of what makes a query good





# Predicting Query Quality with $f_w$

brand_name	class	uses
Humira	TNF inhibitor	rheumatoid arthritis ...



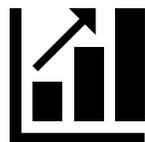
Feedback is used to update  $w$

## Design Challenge:



**Short-Run Success:** find sufficiently good queries quickly

- Users must remain engaged with the system



**Long-Run Success:** should *continue* to improve over time

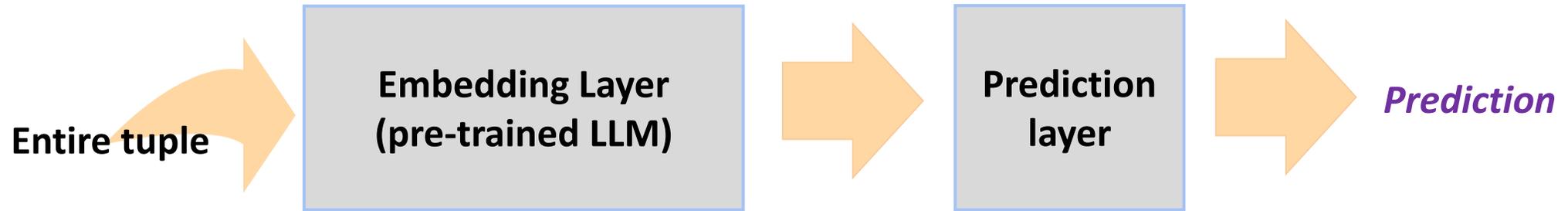
- Fit to domain/diversity of local entities

Leverage  
pretrained LLMs



# Leveraging Pre-trained LLM Priors

High-level idea:



**Online setting:** only know the quality of queries tried

*Exploration:* try new queries that *may* be better

*Exploitation:* use queries known to be good

**$\epsilon$ -greedy:** with  $(1-\epsilon)$  probability, select query with highest predicted quality  
with  $\epsilon$  probability, select random query

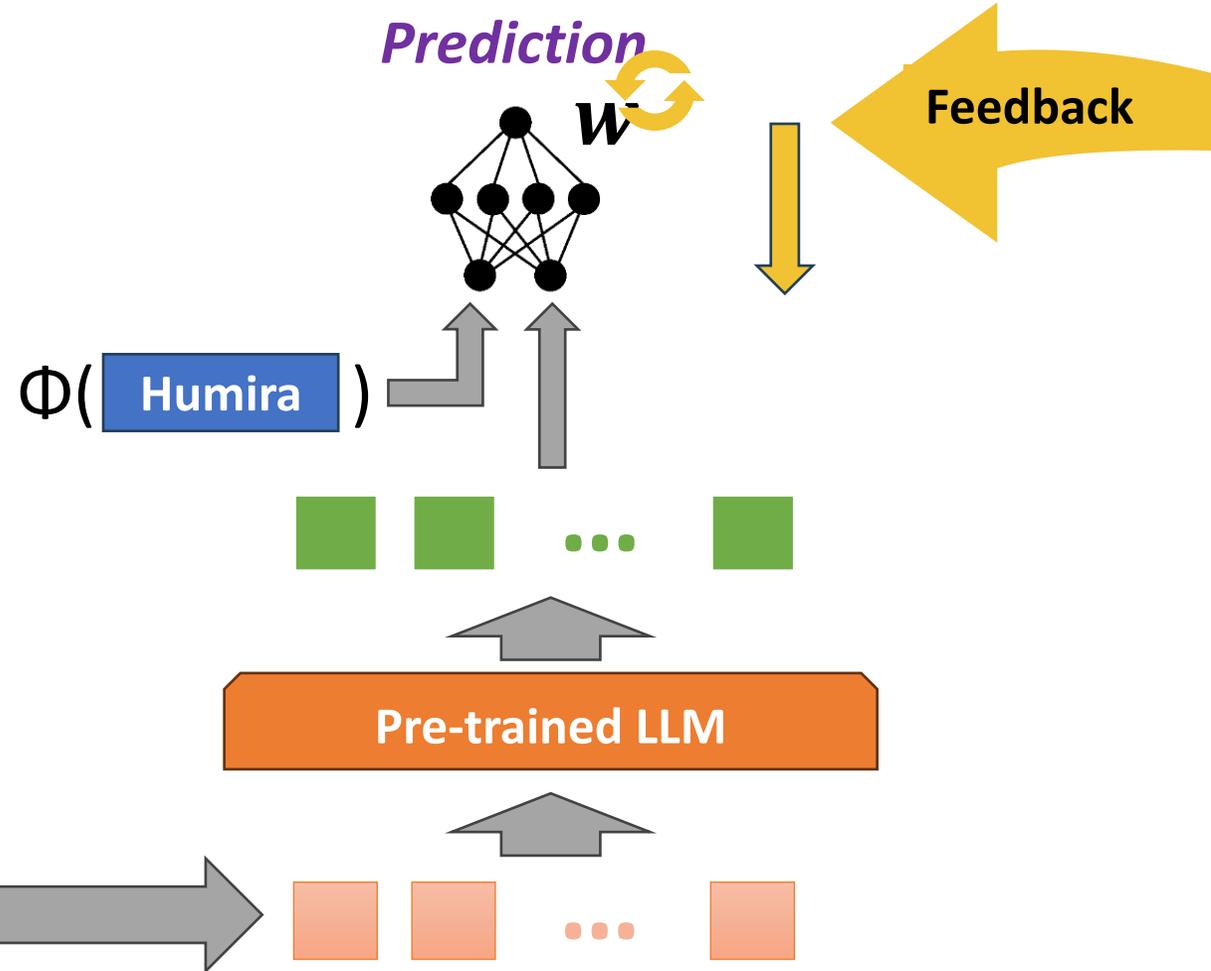


# Model V. 1.0 (Prior Work)

1. Concatenate terms into one string
2. Tokenize and embed
3. Get contextualized embedding
4. Inject features (lexical, distributional, and semantic)
  - Includes structural information
5. Predict quality using MLP head

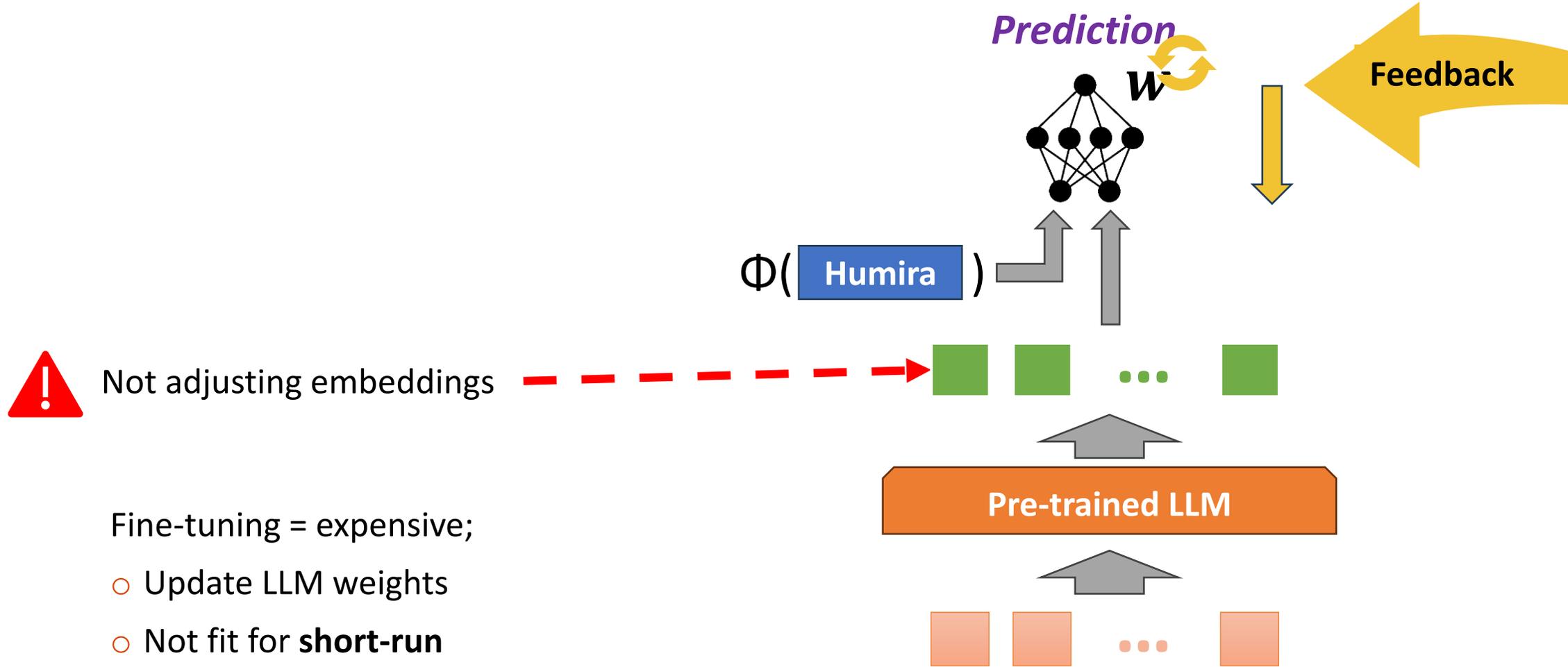
brand_name	class	uses
Humira	TNF inhibitor	rheumatoid arthritis ...

“Humira TNF inhibitor rheumatoid arthritis ...”





# Embeddings Not Aligned With Domain/Task





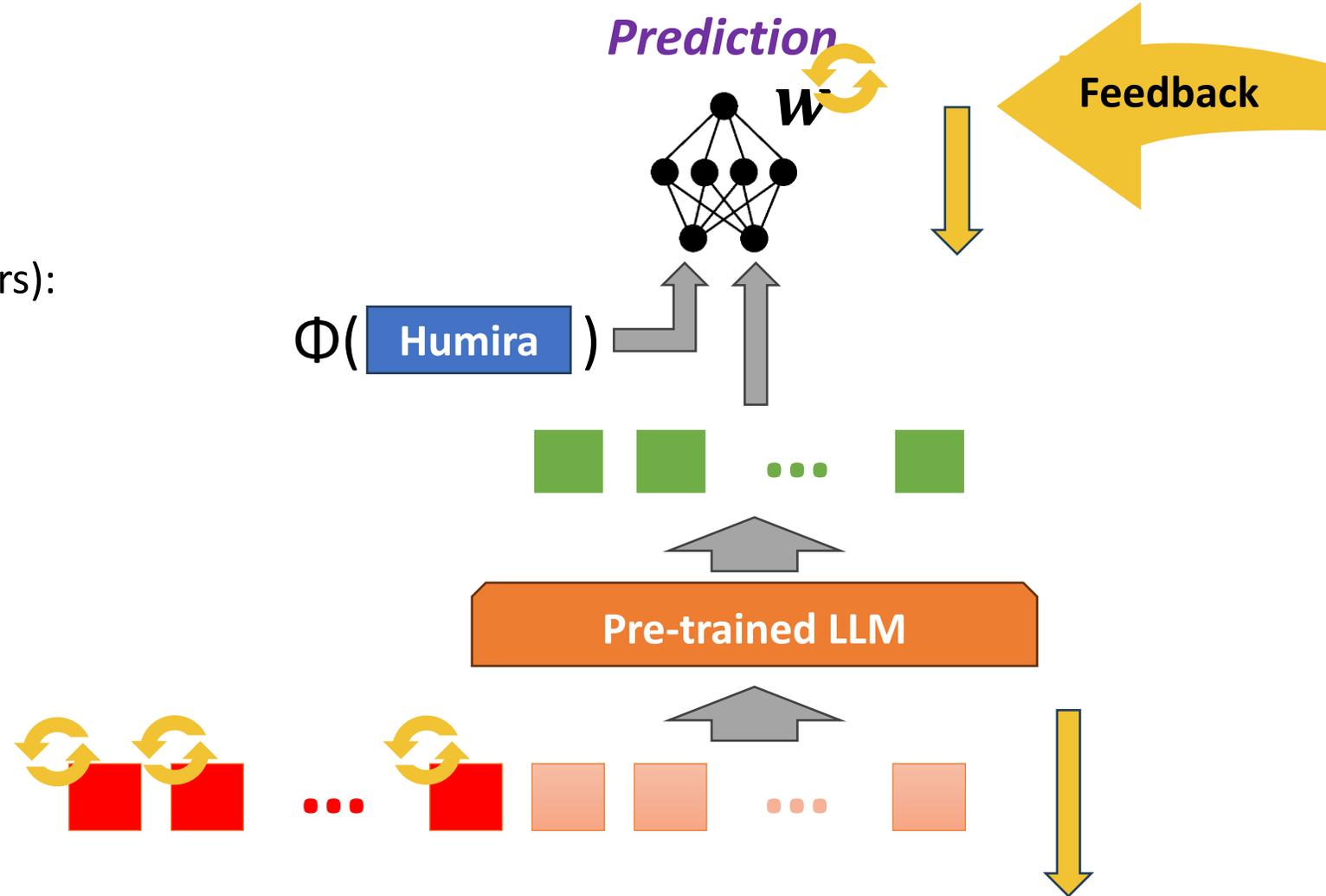
# Prefix Tuning: Tuning for Domain and Task

Parameter-efficient approach:

1.  $p$  "prompts" (continuous vectors):



2. Prepend onto pre-LLM input
  - Learned contextualization

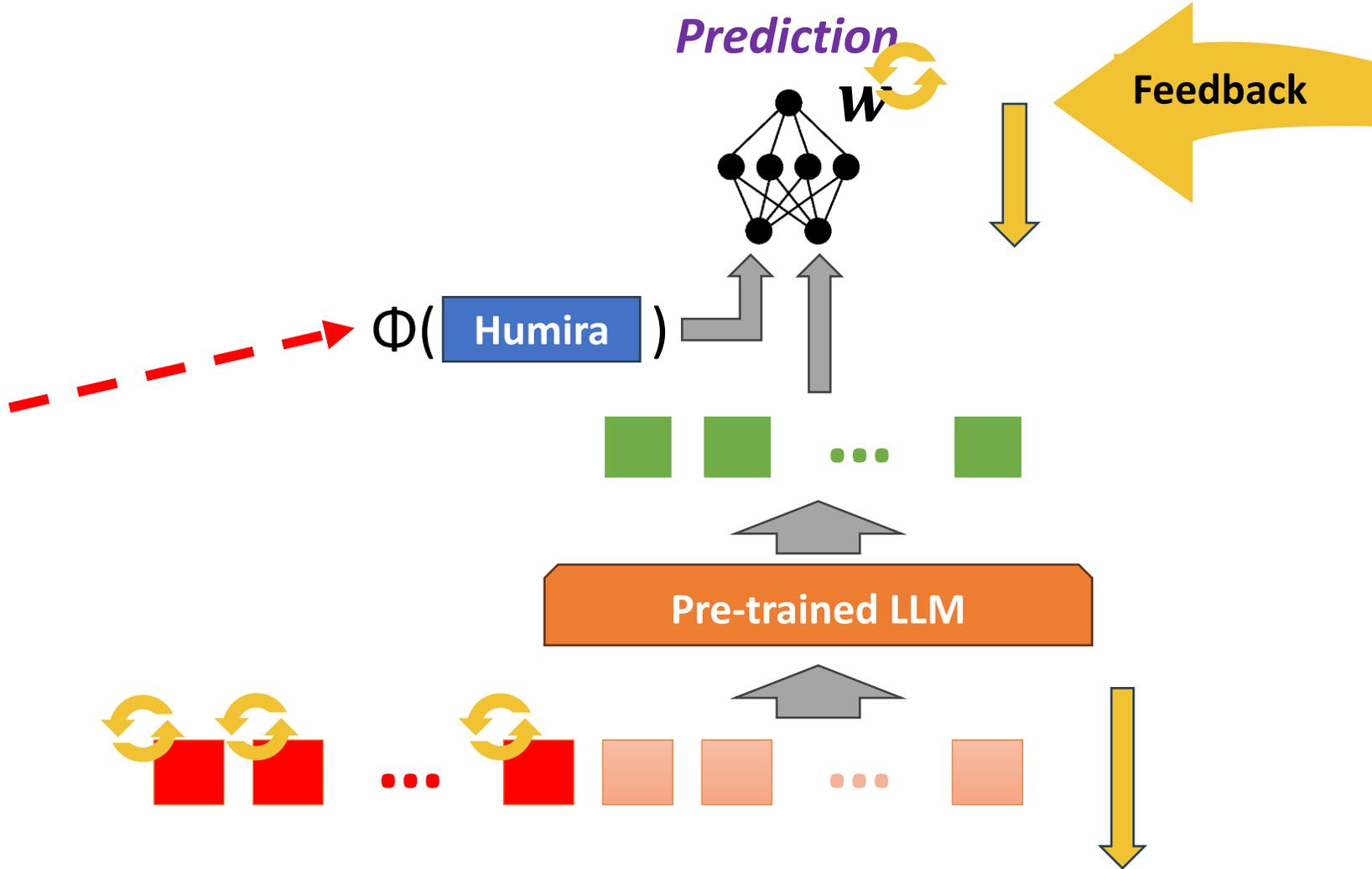




# Structure Introduced Too Late!



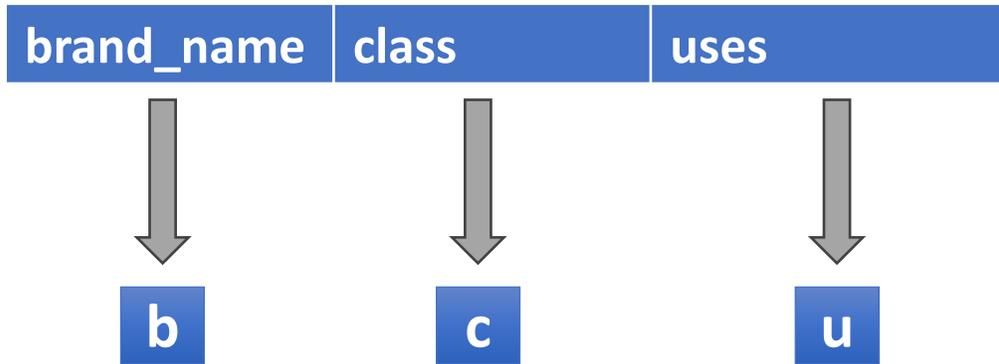
LLM does not “know” about structure



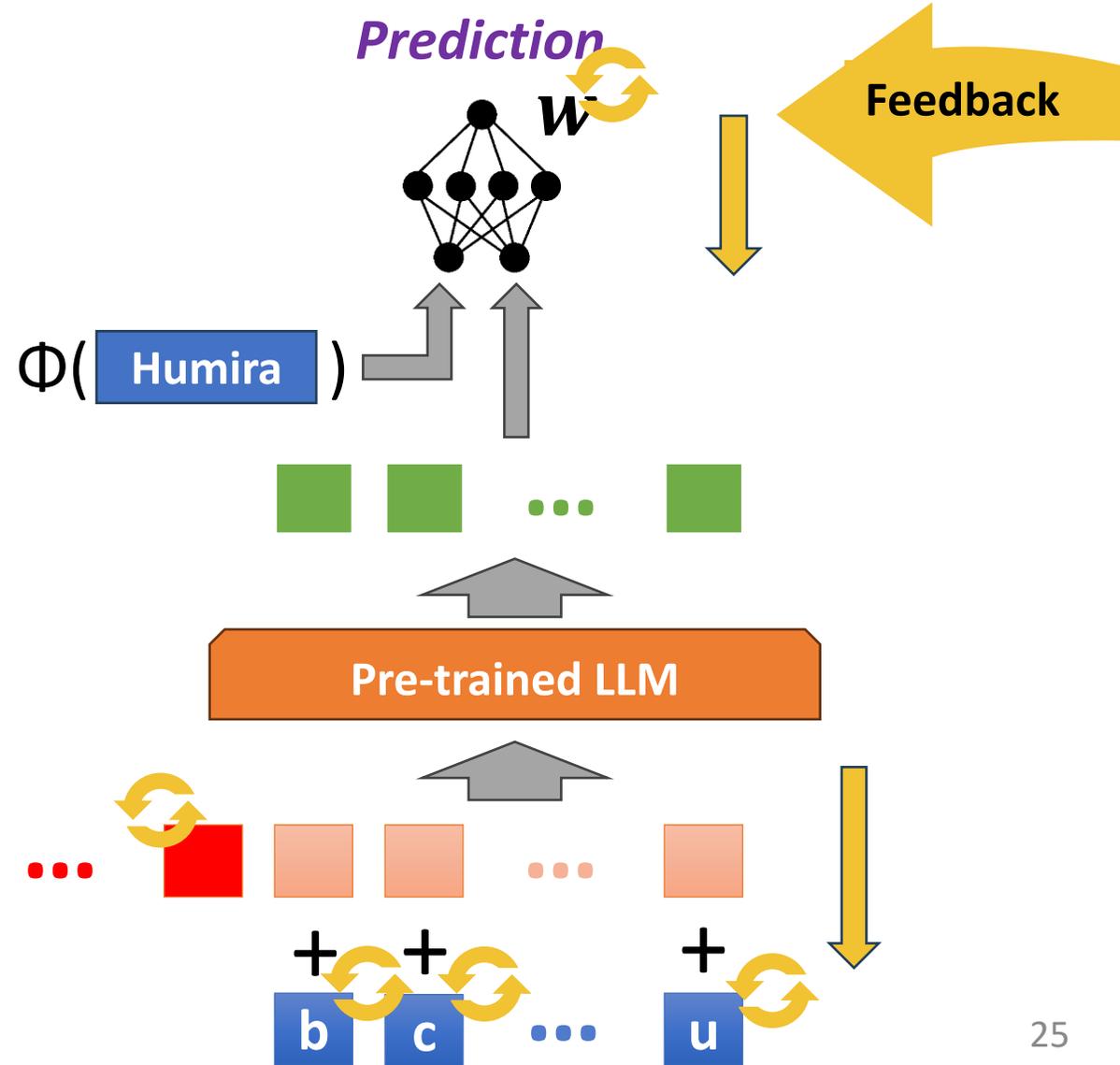
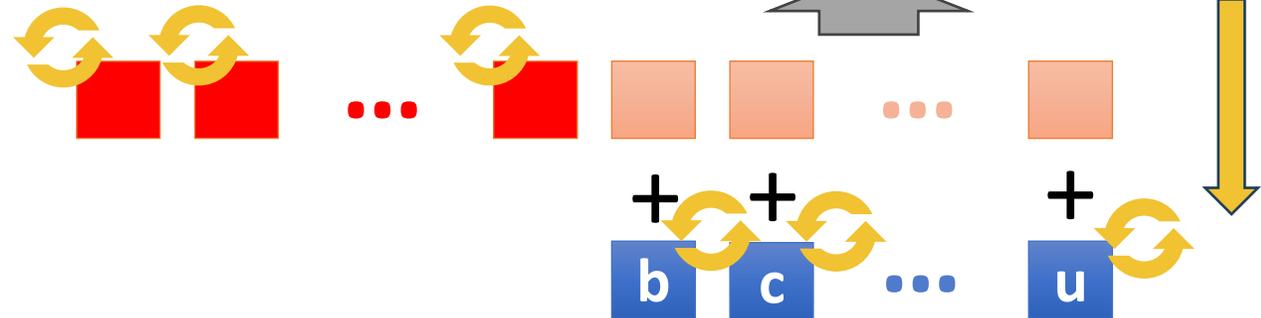


# Attribute Encoding: Fusing Structure with Input

1. Each attribute (column) encoded as a vector



2. Add to pre-LLM input (depending on origin)





# Empirical Study Setup

Dataset	Source	Desc.	#entities
Drugs	Local	Drug reviews	13,725
	External	Wikipedia summaries of drugs	46,976
WDC	Local	Products	57,109
	External	Products	55,247
ChEBI	Local	Molecular information specific to drugs	5,483
	External	Molecules and their effects on living organisms	189,467
CORD-19	Local	Abstract	250,575
	External	Title, authors, etc.,	340,826

Run simulations over variety of domains

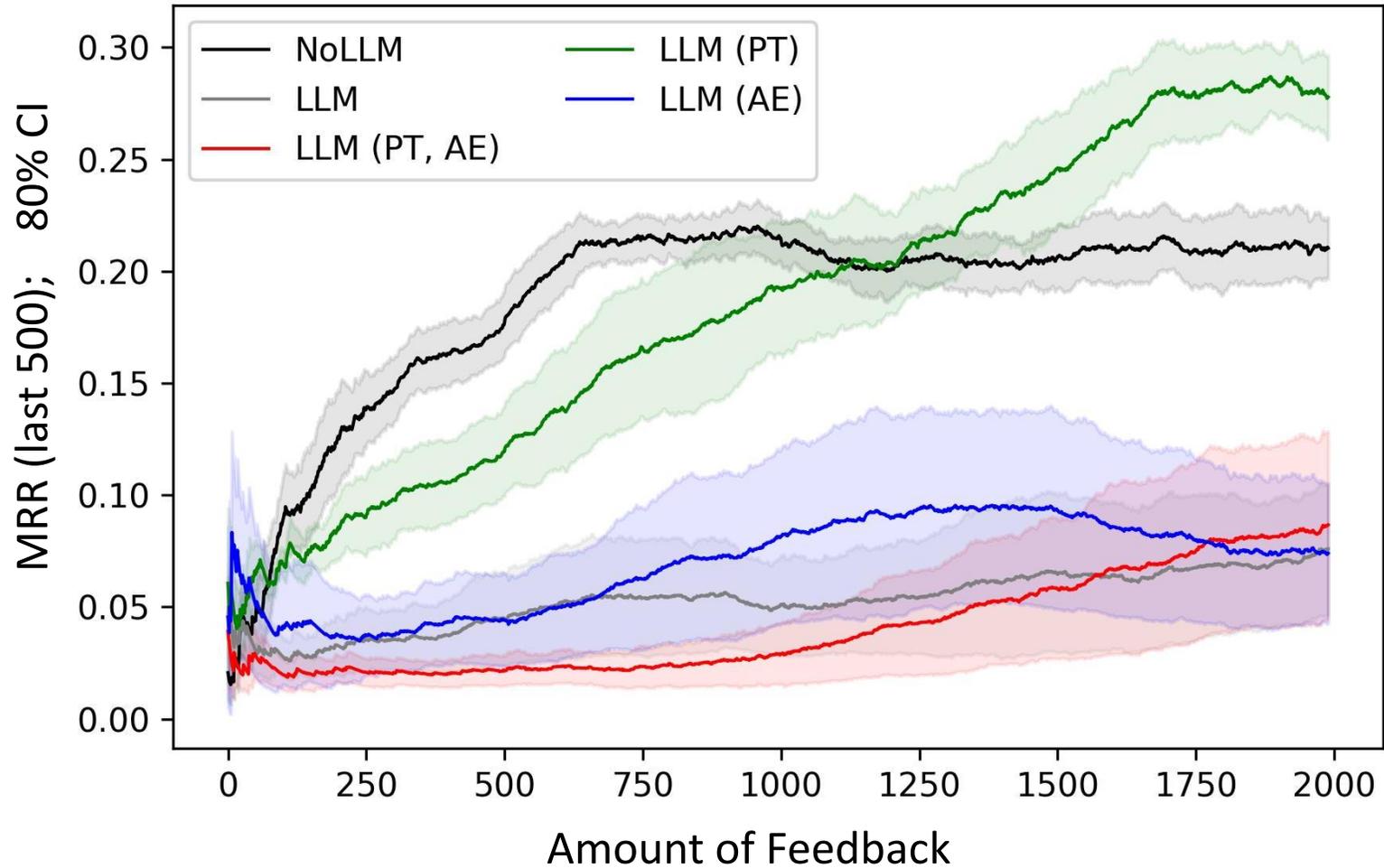
- Ground truth = feedback
- LLM = Longformer

QUESTION:

- Does attribute encoding help?
- Does prefix-tuning help?

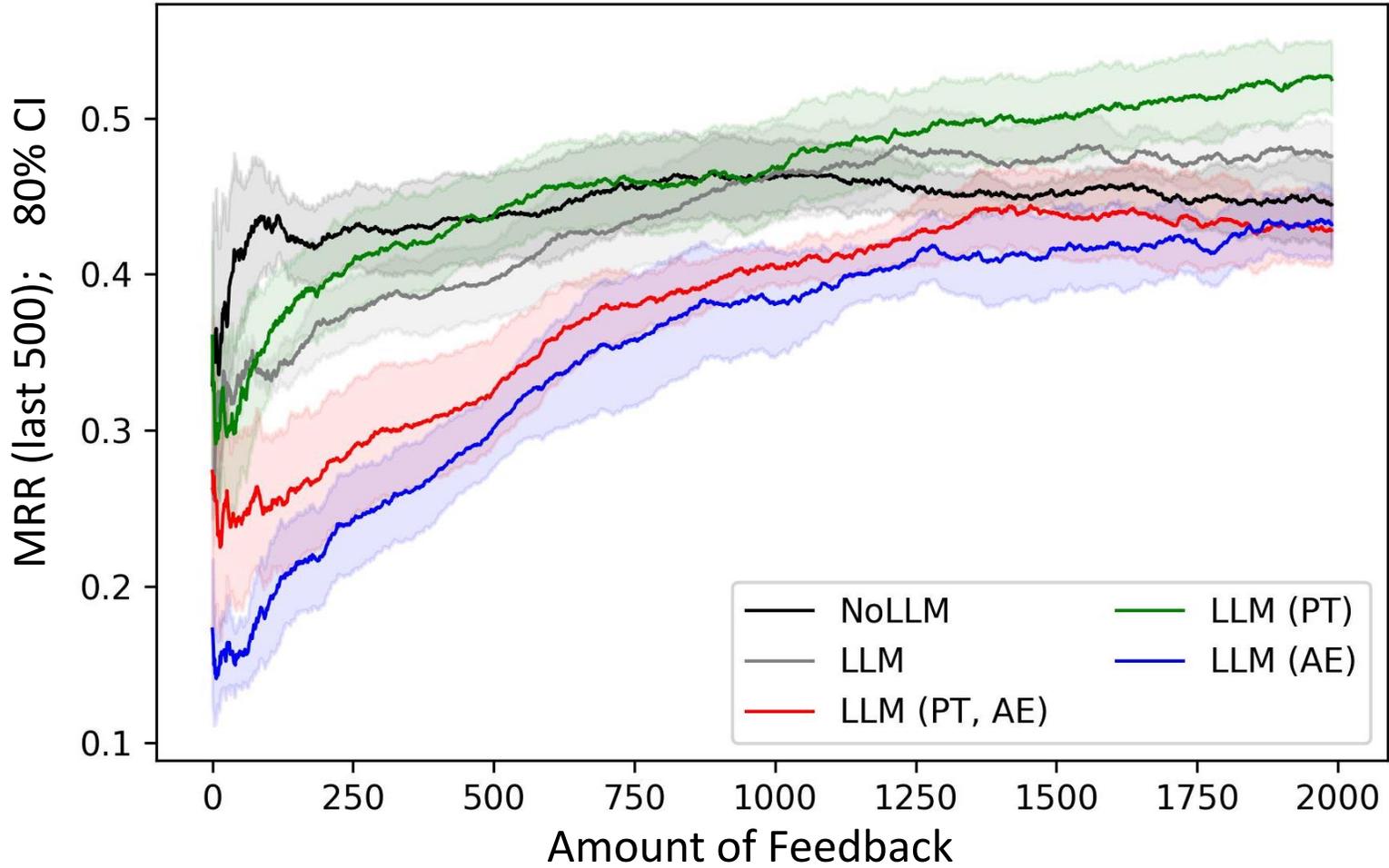


# Comparing Enhancements: CORD-19





# Comparing Enhancements: WDC





# Future Work

- Better fuse domain-specific knowledge with pre-LLM input
- Generate structured queries (SQL, graph-based)
  - Weakly supervised semantic parsing + Short-run challenge = **very hard!!**
  - LLMs have strong performance for few-shot learning
    - Strong prior for complex queries

# Takeaways



## Motivation/Setup

- Mediators require a lot of resources to build/maintain by hand
- Learn the mediator online using user feedback!
- Pre-trained LLM (V. 1) prior



## Enhancements

- Enhancements:
  - Prefix-tuning
  - Attribute encoding



## Experiments

- Prefix-tuning beats or meets V. 1 performance
- Attribute encoding may degrade performance

# Thank you!

## Please share your questions!

